# A NEUROFUZZY EXPERT SYSTEM FOR COMPETITIVE TENDERING IN CIVIL ENGINEERING

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Degree of Doctor of Philosophy in the Faculty of Engineering

**BY**

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# DECLARATION

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other University or other institution of learning.

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# ABSTRACT

Competitive tendering is one of the most critical activities of contractors in the construction industry. A contractor must first decide whether to bid or not for a new project. If the "bid" decision was made, a cost estimate needs to be produced considering uncertainties involved in pricing the required materials, plant and labour and, thereafter, a mark up should be determined and added to the cost estimate as a coverage of profit and an allowance for unexpected risks. The tendering decisions; i.e. whether or not to bid and how much to mark up the estimated cost, are very important as they have profound effects on the day-to-day operations and the long-term performance of the construction firm. The importance of these two decisions lies in the fact that the success of a construction organisation is dependent on their outcomes. Additionally, these decisions are very complex because they are liable to be affected by many internal and external factors. In practice, however, the bidding decisions are usually made in a largely subjective manner. The absence of a suitable structured basis often results in mistakes causing loss to contractors and adversely affecting the industry. The main objective of the present study is to develop a simple-to-use tendering strategy model for possible implementation in the Syrian construction industry. During the last fifty years, many attempts have been made to model the process of making the bidding decisions. The majority of the developed models were based of the probability and the utility theories. The mathematical complexity of these modes, their over-simplified assumptions, and the necessity of historical data made them inapplicable in the construction industry. Other models were developed using regression analysis and multi-criteria decision analysis techniques. These models have many advantages over the probability and utility models. For example, they represent the bidding process more realistically as they account for multiple factors that affect this process. Also, the expert systems and the artificial neural network techniques were applied to the bidding process and helped to achieve some improvement over previous models. More recently, many researchers have proposed bidding strategies based on the fuzzy set theory. They claimed that fuzzy set theory is very suitable for the subjective nature of the tendering decisions. However, there is not a strong agreement among researchers on which modelling technique is the best for developing practical and more applicable tendering models. Therefore, based on the literature

review, the modelling techniques that proved to be useful in previous studies were selected and used in the current work. These are regression analysis, decision analysis, and the artificial neural network techniques. The neural networks model was more reliable compared with the other models. Attempting to achieve more improvements, a new technology called neurofuzzy was implemented. This technology is a combination of neural networks and fuzzy expert systems. The application of this powerful tool has enabled an innovative tendering strategy model to be developed. This model has numerous advantages over all previous bidding models. It was implemented in a user-friendly computer prototype called NET (Neurofuzzy Expert systems for competitive Tendering in civil engineering). Testing NET on real life bidding situations provided evidence that it could be used in practice with great confidence. Unlike most previous bidding strategy models, NET can provide guidance in making the "bid/no bid" decision and in setting a suitable mark up size. This model provides civil engineering contractors with a standard methodology to improve the quality of their tendering decisions. It does not require any historical data about previous projects or potential competitors. Also, the user does not need to perform any mathematical computations. All he/she needs is to provide his/her subjective assessments of the bidding situation under consideration. In addition to all these advantages, the proposed model can be modified very easily to suit certain tendering policies by learning from new examples, adding new rules to the knowledge base, removing existing rules or fine-tuning their associative importance.

# TABLE OF CONTENT


| | Page |
|---|---|
| Declaration | (I) |
| Acknowledgements | (II) |
| Abstract | (III) |
| Table of Contents | (V) |
| List of Figures | (X) |
| List of Tables | (XIV) |
| List of Symbols and Abbreviations | (XVI) |

**CHAPTER 1: INTRODUCTION** **01**

1.1 Introduction 01
1.2 Theoretical Background 02
1.3 Need for Practical Bidding Models 05
1.4 Objectives of the Study 08
1.5 Methodology 09
1.6 Outline of the Thesis 12

**CHAPTER 2: RELEVANT DECISIO-MAKING TECHNIQUES: A REVIEW** **15**

2.1 Introduction 15
2.2 Basic Concepts of Probability Theory 16
2.3 Basic Concepts of Utility Theory 17
2.4 Multicriteria Decision Analysis Theory 19
2.5 Basics of Regression Analysis Techniques 21
2.6 Artificial Intelligence Techniques 24
2.6.1 Expert Systems 25
2.6.1.1 Components of an Expert System 26
2.6.1.1.1 Knowledge Base 27
2.6.1.1.2 Inference Mechanism 27
2.6.1.1.3 User Interface 28
2.6.1.1.4 Explanation Facility 28
2.6.1.2 Expert Systems Development 29
2.6.1.3 Advantages and Disadvantages of Expert Systems 30
2.6.1.4 Expert Systems Applications in Construction 30
2.6.2 Artificial Neural Networks 31
2.6.2.1 Applications of ANN in Construction 33
2.7 Expert Systems vs Neural Networks 34
2.8 Basic Concepts of Fuzzy Set Theory 35
2.8.1 What is Fuzzy Logic? 36
2.8.1.1 Fuzzification 38
2.8.1.2 Fuzzy Logic Inference 39
2.8.1.2.1 Premise Aggregation 39
2.8.1.2.2 Result Aggregation 41
2.8.1.3 Defuzzification 42
2.8.2 Applications of Fuzzy Logic in Construction 44
2.8.3 Neurofuzzy Modelling 45
2.9 Summary 47

**CHAPTER 3: PREVIOUS BIDDING STRATEGIES** 49
3.1 Introduction 49
3.2 Current Bidding Strategy Models 49
3.2.1 Bid/No Bid Models 50
3.2.2 Mark up Models 54
3.2.2.1 Traditional Models 54
3.2.2.1.1 Probabilistic Bidding Strategy Models 54
3.2.2.1.2 The Expected Utility Value Models 56
3.2.2.1.3 Other Approaches 57
3.2.2.2 Regression Mark up Models 58
3.2.2.3 ANN and ES Mark up Models 58
3.2.2.4 Models Based on Fuzzy Set Theory 61
3.2.3 "Bid/No Bid and Mark up" Models 64
3.3 Summary and Conclusions 65

**CHAPTER 4: DATA ELICITATION AND ANALYSIS** 68
4.1 Introduction 68
4.2 Theoretical Background 68
4.3 Data Collection Methods 69
4.3.1 Questionnaire Survey 69
4.3.2 Interviews 70
4.4 Semi-Structured Interviews 73
4.5 Questionnaire Survey 73
4.5.1 Questionnaire A 74
4.5.1.1 The Development of Questionnaire A 74
4.5.1.2 Structure of Questionnaire A 75
4.5.1.3 Sample Selection and Response Rate 77
4.6 Interviews Findings: The Current Bidding Practice in Syria 78
4.7 Interviews Findings: Crucial effect of Some Individual "Bid/No Bid" Factors 82
4.8 Interviews Findings: The Components of the Mark up 83
4.9 Interviews Findings: Modifications to the Formal Questionnaire 83
4.10 Findings of Questionnaire A: Background Information 84
4.11 Findings of Questionnaire A: Importance of "Bid/No Bid" factors 87
4.12 Findings of Questionnaire A: Importance of Mark up factors 92
4.13 Findings of Questionnaire A: Neutral Scores of the "Bid/No Bid" factors 94
4.14 Selection of the Most Important "Bid/No Bid" factors 95
4.15 Selection of the Most Important Mark up factors 96
4.16 Questionnaire B 97
4.16.1 Results of Questionnaire B: General Information 98
4.16.2 Results of Questionnaire B: Influence of the "Bid/No Bid" factors 99
4.16.3 Results of Questionnaire B: Influence of the Mark up Factors 101
4.16.4 Results of Questionnaire B: Cause Effect Analysis 102
4.17 Summary 110

**CHAPTER 5: A PARAMETRIC AND REGRESSION BIDDING STRATEGY** **111**
5.1 Introduction
5.2 The Modelling Methodology 111
5.3 Bid/No Bid Development 114
5.3.1 Selection of the Input factors 114
5.3.2 Development of a Bidding Index 117
5.3.3 A Parametric Bid/No Bid Model 122
5.3.3.1 Sensitivity Analysis 125
5.3.3.2 Model Optimisation 127
5.3.3.3 Degree of Confidence 131
5.3.3.4 Testing and Validation 133
5.4 Mark up Development 134
5.4.1 Selection of Input Variables 134
5.4.2 Mark up Selection: A Linear regression Approach 134
5.4.3 Mark up Selection: A Non-Linear regression Approach 136
5.4.4 Selection of the Final Regression Mark up Model 137
5.4.5 Sensitivity Analysis 138
5.5 A Parametric and Regression Bidding Strategy Model 139
5.6 Discussion 140
5.7 Summary 142

**CHAPTER 6: NEURAL NETWORK BIDDING MODEL** **144**
6.1 Introduction 144
6.2 Why ANN? 145
6.3 Methodology 145
6.4 Development of ANN "Bid/no Bid" Model 146
6.4.1 The Modelling Process 147
6.4.1.1 Data Preprocessing 148
6.4.1.1.1 Selection of the Input Variables 150
6.4.1.2 Initial Design Decisions 153
6.4.1.3 Training 156
6.4.1.4 Testing 157
6.4.1.5 Modifications 158
6.4.1.6 Model selection 166
6.4.2 The Selected "Bid/No Bid" Model 170
6.4.2.1 Degree of Confidence 172
6.4.2.2 The Effect of Input Variables on the "Bid/No Bid" Decision 175
6.4.2.3 Testing and Validation 178
6.5 Development of ANN Mark up Model 180
6.5.1 Data Preprocessing 180
6.5.1.1 Selection of the Input Variables 181
6.5.2 Initial Design Decisions 182
6.5.3 Training 184
6.5.4 Testing 184
6.5.5 Modification 185
6.5.6 Model Selection 186
6.5.7 The Selected Mark up Model 190
6.5.7.1 Sensitivity Analysis 192

6.5.7.2 Testing and Validation 195
6.6 An Integrated ANN Bidding Strategy Model 196
6.7 Summary and Discussion 196

**CHAPTER 7: A NEUROFUZZY EXPERT SYSTEM FOR COMPETITIVE TENDERING 198**
7.1 Introduction 198
7.2 Development of a Neurofuzzy "Bid/no Bid" Model 198
7.2.1 Initial Design 199
7.2.2 Training 203
7.2.3 Testing 204
7.2.4 Modification 205
7.2.5 Model Selection 212
7.2.6 The Final Fuzzy Logic "Bid/No Bid" Model 212
7.2.7 Confidence Degree Sub-Model 216
7.2.8 Sensitivity Analysis 218
7.2.9 Testing and Validation 223
7.3 A Neurofuzzy Model for Mark up Selection 225
7.3.1.1 Sensitivity Analysis 233
7.3.1.2 Testing and Validation 235
7.4 Summary 236

**CHAPTER 8: MODEL SELECTION 237**
8.1 Introduction 237
8.2 Development of the Selection Criteria 237
8.3 Model Selection 240
8.3.1 The Final "Bid/No Bid" Model 240
8.3.2 The Final Mark up Model 244
8.3.3 t-test for Paired Samples 248
8.4 An Integrated Neurofuzzy Bidding Strategy Model 250
8.5 A Basic Model for Producing the Final Bid Price 252
8.6 NET: A Neurofuzzy Expert System for Competitive Tendering in Civil Engineering 253
8.7 Summary 257

**CHAPTER 9: DISCUSSION 259**
9.1 Introduction 259
9.2 Factors Affecting the Bidding Decisions 259
9.2.1 Bid/No Bid Factors 261
9.2.2 Mark up Factors 262
9.2.3 Method of Analysis 263
9.3 Modelling Techniques 264
9.4 Scope 271
9.5 Conclusion 272

**CHAPTER 10: SUMMARY AND CONCLUSIONS 274**
10.1 Summary 274
10.2 Contributions 275
10.3 Other Contributions 277

10.4 Limitations 279
10.5 Recommendations for Further Research 279

**REFERENCES** **281**

**APPENDIX A:** Questionnaire survey (A) **291**
**APPENDIX B:** Questionnaire survey (B) **300**
**APPENDIX C:** Non-linear regression equations **303**
**APPENDIX D:** Concepts used in developing the ANN bidding models **307**
**APPENDIX E:** Related publications **319**

# LIST OF FIGURES


| | Page |
|---|---|
| Figure 1.1 Phases of civil engineering projects | 02 |
| Figure 1.2 Overview of the bidding process | 05 |
| Figure 1.3 Outline of the research methodology | 10 |
| Figure 1.4 Outline of the thesis | 13 |
| Figure 2.1 Types of utility functions | 17 |
| Figure 2.2 Utility functions for loss, overhead, and profit | 18 |
| Figure 2.3 The combined utility function | 18 |
| Figure 2.4 Final expected utility curve | 19 |
| Figure 2.5 A tree diagram for the AHP | 20 |
| Figure 2.6 Examples of linear and non-linear statistical relations | 22 |
| Figure 2.7 The base of regression equations | 22 |
| Figure 2.8 Trustworthy of regression equations | 23 |
| Figure 2.9 The architecture of an expert system | 26 |
| Figure 2.10 A functional model of a processing element | 31 |
| Figure 2.11 Different types of transfer functions | 32 |
| Figure 2.12 The general structure of a multi-layer perceptron | 33 |
| Figure 2.13 Architecture of a fuzzy logic system | 37 |
| Figure 2.14 Fuzzy logic algorithm | 37 |
| Figure 2.15 Transfer characteristics of the Min operator | 40 |
| Figure 2.16 Transfer characteristics of the Mix operator | 40 |
| Figure 2.17 The fuzzy logic MinMax aggregation operator | 40 |
| Figure 2.18 Transfer characteristic of the Gamma operator with $\gamma = 0.3$ | 41 |
| Figure 2.19 Transfer characteristic of the MinAvg operator with degree of compensation (1), i.e. extreme AND. | 41 |
| Figure 2.20 Centre of Maximum defuzzification method | 43 |
| Figure 2.21 Centre of area (CoA) defuzzification method | 43 |
| Figure 2.22 Mean of Maximum defuzzification method | 44 |
| Figure 2.23 Mapping a neural network to a fuzzy logic system | 46 |
| Figure 2.24 Integrating neural networks with fuzzy logic | 47 |
| Figure 3.1 Attribute hierarchy for "bid/no bid" decision problem | 51 |
| Figure 3.2 Components of bidding strategy model (Fayek, 1996) | 63 |
| Figure 4.1 Components of the questionnaire design process | 71 |
| Figure 4.2 The practice of making the bidding decisions | 76 |
| Figure 4.3 The development of questionnaire A | 81 |
| Figure 4.4 Typical projects undertaken by participants | 84 |
| Figure 4.5 Typical size of projects undertaken by participants | 85 |
| Figure 4.6 Minimum capital required to bid on a new project | 85 |
| Figure 4.7 Current degree of competition | 86 |
| Figure 4.8 Average number of competitors | 86 |
| Figure 4.9 Experience of the surveyed contractors | 88 |
| Figure 4.10 Profiles of ten important bid/no bid factors | 91 |
| Figure 4.11 Profiles of ten important mark up factors | 93 |
| Figure 4.12 Selection of the most important bid/no bid factors | 96 |
| Figure 4.13 Selection of the most important mark up factors | 97 |
| Figure 4.14 Influence of the bid/no bid factors | 100 |
| Figure 4.15 Influence of the mark up factors | 102 |

Figure 4.16 Relationship between bid/no bid decision and fulfilment of the To-tender conditions 104
Figure 4.17 Relationship between bid/no bid decision and site accessibility 104
Figure 4.18 Relationship between bid/no bid decision and site clearance of obstructions 104
Figure 4.19 Relationship between bid/no bid decision and availability of capital 104
Figure 4.20 Relationship between bid/no bid decision and availability of materials 105
Figure 4.21 Relationship between bid/no bid decision and proportions that can be constructed mechanically 105
Figure 4.22 Relationship between bid/no bid decision and confidence in the cost estimate 105
Figure 4.23 Relationship between bid/no bid decision and financial capability of the client 105
Figure 4.24 Relationship between bid/no bid decision and public objection 106
Figure 4.25 Relationship between bid/no bid decision and current workload 106
Figure 4.26 Relationship between bid/no bid decision and relations with/ reputation of the client 106
Figure 4.27 Relationship between bid/no bid decision and favourability of expected cash flow 106
Figure 4.28 Relationship between mark up and the expected risks 107
Figure 4.29 Relationship between mark up and the equipment owned 107
Figure 4.30 Relationship between mark up and the confidence in the cost estimate 107
Figure 4.31 Relationship between mark up and the availability of materials 107
Figure 4.32 Relationship between mark up and the competence of the expected competitors 108
Figure 4.33 Relationship between mark up and degree of buildability 108
Figure 4.34 Relationship between mark up and competition 108
Figure 4.35 Relationship between mark up and proportions that can be constructed mechanically 108
Figure 4.36 Relationship between mark up and rigidity of specifications 109
Figure 4.37 Relationship between mark up and site clearance of obstructions 109
Figure 4.38 Relationship between mark up and site accessibility 109

Figure 5.1 Development of a parametric and regression bidding strategy model 113
Figure 5.2 A parametric model of a positive factor 118
Figure 5.3 Contribution of the "availability of materials" factor in the "Bid" recommendation 118
Figure 5.4 A parametric model of a negative factor 119
Figure 5.5 Contribution of the "public objection" factor in the "Bid" recommendation 120
Figure 5.6 Production of the bidding index 121
Figure 5.7 Bid or no bid conditions 122
Figure 5.8 A flowchart model of "bid/no bid" decision 124
Figure 5.9 Sensitivity of the bidding index to changes in individual factors 126
Figure 5.10 Optimum values of $B_i$ and $B_j$ 129
Figure 5.11 Selection of the optimum cut-off point between "Bid" and "No Bid" 130
Figure 5.12 Confidence degree based on the bidding index 132
Figure 5.13 Actual and predicted mark up size 138
Figure 5.14 An integrated parametric and regression bidding strategy model 141

Figure 5.15 Effect of the "project size" factor on the "bid" decision 141
Figure 6.1 General methodology for developing ANN models 147
Figure 6.2 Framework of developing ANN models 148
Figure 6.3 Format of training/testing files 150
Figure 6.4 Input factors to be considered in developing the ANN "bid/no bid" model 151
Figure 6.5 Binary input mode 154
Figure 6.6 Structure of the initial ANN "bid/no bid" model 156
Figure 6.7 A summary flowchart of training and testing 158
Figure 6.8 Effect of number of PEs in one hidden layer 159
Figure 6.9 Effect of number of PEs in second hidden layer with 5 PEs in the first one 160
Figure 6.10 Effect of number of PEs in second hidden layer with 10 PEs in the first one 160
Figure 6.11 Effect of number of PEs in second hidden layer with 15 PEs in the first one 161
Figure 6.12 Selection of the best structure of hidden PEs 161
Figure 6.13 Selection of the best learning rule 162
Figure 6.14 Selection of the best transfer function 162
Figure 6.15 Selection of the best Epoch size 162
Figure 6.16 Selection of the best Momentum 163
Figure 6.17 Selection of the best learning coefficient 163
Figure 6.18 Selection of the best ANN "bid/no bid" model 169
Figure 6.19 Structure of the final ANN "bid/no bid" model 170
Figure 6.20 Parameters of the "bid/no bid" decision 173
Figure 6.21 The best cut-off point between "bid" and "no bid" 173
Figure 6.22 Confidence degree based on the neural bidding index 175
Figure 6.23 Effect of individual inputs on the ANN "bid/no bid" model's output 177
Figure 6.24 Actual and predicted decisions of the test projects 179
Figure 6.25 Structure of the initial ANN mark up model 182
Figure 6.26 Selection of the best ANN mark up model 189
Figure 6.27 Structure of the final ANN mark up model 191
Figure 6.28 Sensitivity of the ANN and the non-linear regression mark up Models to changes in individual input factors 194
Figure 7.1 Framework of the development process 199
Figure 7.2 The general structure of a fuzzy logic systems 200
Figure 7.3 The "accessibility" input linguistic variable 201
Figure 7.4 Linguistic variable for the output variable "NFBI" 201
Figure 7.5 The general structure of model 1 202
Figure 7.6 Model 1 before training 204
Figure 7.7 Model 1 after training 204
Figure 7.8 The modification process 207
Figure 7.9 Examining different parameters for the Min-Max operator 208
Figure 7.10 Examining different parameters for the Min-Avg operator 208
Figure 7.11 Examining different parameters for the "γ" operator 208
Figure 7.12 Selection of the best operator and parameter 209
Figure 7.13 Examining different numbers of input terms 209
Figure 7.14 Selection of the best result aggregation method 210
Figure 7.15 Examining different defuzzification method 210
Figure 7.16 Examining different number of input terms 210

Figure 7.17 Selection of the output membership function shape 211
Figure 7.18 Selection of the final neurofuzzy "bid/no bid" model 212
Figure 7.19 Structure of the final neurofuzzy "bid/no bid" model 213
Figure 7.20 MBFs of the "workload" input variable 213
Figure 7.21 MBFs of the output variable "NFBI" 216
Figure 7.22 Selection of the best cut-off point between "bid" and "no bid" 217
Figure 7.23 Confidence degree based on the neurofuzzy bidding index 217
Figure 7.24 Sensitivity of the neurofuzzy "bid/no bid" model to changes in individual input variables 220
Figure 7.25 Effect of individual inputs on the neurofuzzy "bid/no bid" model's output 221
Figure 7.26 Relationship between "fulfilment of the to-tender conditions", "relation with/reputation of the client", and the "NFBI" 222
Figure 7.27 Relationship between "fulfilment of the to-tender conditions", "current workload", and the "NFBI" 223
Figure 7.28 Actual and predicted "bid/no bid" decisions 224
Figure 7.29 Examining different number of input terms for the mark up model 225
Figure 7.30 Examining different number of output terms for the mark up model 227
Figure 7.31 Examining different defuzzification methods for the mark up model 227
Figure 7.32 Examining different shapes of membership functions for the mark up model 227
Figure 7.33 Selection of the final fuzzy mark up model 228
Figure 7.34 Structure of the final fuzzy logic mark up model 229
Figure 7.35 MBFs of the "risks expected" input variable 229
Figure 7.36 MBFs of the output variable "Mark up" 232
Figure 7.37 Comparison between the sensitivity of the neurofuzzy and the ANN mark up models to changes in their input variables 234
Figure 7.38 Actual and predicted mark ups of the validation cases 236

Figure 8.1 The total worth of the "bid/no bid" models 242
Figure 8.2 Relations between the mark ups predicted by the developed models And the actual mark ups of the test cases 244
Figure 8.3 Error measurements of the mark up models 245
Figure 8.4 The total worth of the developed mark up models 246
Figure 8.5 Testing the difference between the actual and the predicted mark up 248
Figure 8.6 comparison between the mark up models 249
Figure 8.7 Testing the difference between the mark up models 250
Figure 8.8 Flowchart of the final integrated bidding strategy model 251
Figure 8.9 Calculation of the tender price 253
Figure 8.10 General information about the considered project 254
Figure 8.11 subjective assessment of the "bid/no bid" criteria 254
Figure 8.12 Bid or No Bid recommendation 255
Figure 8.13 subjective assessment of the mark up criteria 255
Figure 8.14 Direct and indirect cost estimation 256
Figure 8.15 The final output screen 257

Figure 9.1 Comparison between the accuracy of NET and previous models 268
Figure 9.2 Relationship between actual mark up values and the prediction error 268
Figure 9.3 Sensitivity of the neurofuzzy bid/no bid model to changes in its inputs 269
Figure 9.4 Sensitivity of the neurofuzzy mark up model to changes in its inputs 270
Figure 9.5 Sensitivity of the non-linear mark up model to changes in its inputs 270
Figure 9.6 Sensitivity of the ANN mark up model to changes in its inputs 271

# LIST OF TABLES

Page
Table 4.1 Kill-scores of positive "bid/no bid" factors 82
Table 4.2 Kill-scores of negative "bid/no bid" factors 82
Table 4.3 The use of mathematical bidding models in various countries 87
Table 4.4 Bid/no bid factors in a descending order of importance 90
Table 4.5 Mark up factors in a descending order of importance 92
Table 4.6 Neutral scores of the positive "bid/no bid" factors 95
Table 4.7 Neutral scores of the negative "bid/no bid" factors 95
Table 4.8 The influence of the most important "bid/no bid" factors 99
Table 4.9 The influence of the most important mark up factors 102

Table 5.1 Parameters of the positive bidding factors 116
Table 5.2 Parameters of the negative bidding factors 116
Table 5.3 Sensitivity of the parametric model to changes in individual factors 126
Table 5.4 Model sensitivity to omitting some factors 127
Table 5.5 Selection of the best values for $B_i$ and $B_j$ 128
Table 5.6 Selection of the best cut-off point between "bid" and "no bid" 130
Table 5.7 Linguistic/percentage confidence degree 132
Table 5.8 Twenty real life bidding situations 133
Table 5.9 Comparison between different regression models 135
Table 5.10 Selection of input variables for the linear regression model 135
Table 5.11 Comparison between linear and non-linear regression mark up models 138
Table 5.12 Sensitivity of the non-linear model to variations in its inputs 139

Table 6.1 Correlation between the most influential bidding factors and the "bid/no bid" decision 152
Table 6.2 Selection of potential input variables for the ANN "bid/no bid" model 153
Table 6.3 The modification process 165
Table 6.4 Selection of the best ANN "bid/no bid" model 167
Table 6.5 The main characteristics of model (B. net 54) 171
Table 6.6 The "MinMax Table" used in model (B. net 54) 171
Table 6.7 Connection weights between the "bid/no bid" model processing elements 171
Table 6.8 Scaling the real-world values to the desired values 172
Table 6.9 Setting the best cut-off point between "bid" and "no bid" spaces 173
Table 6.10 Sensitivity of the ANN model output to changes in individual inputs 177
Table 6.11 Actual and predicted decisions of twenty unforeseen bidding situations 179
Table 6.12 Correlation between the mark up factors 183
Table 6.13 Sets of input variables with different degrees of inter-correlation 183
Table 6.14 Parameters of model M.net 1 184
Table 6.15 The modification process of developing ANN mark up model 187
Table 6.16 Selection of the best ANN mark up model 188
Table 6.17 Selection of the final ANN mark up model 190
Table 6.18 Connection weights between the mark up model processing elements 191
Table 6.19 The "MinMax Table" used in model (M. net 48) 192
Table 6.20 Target network ranges used in model (M. net 48) 192
Table 6.21 Scaling the input real-world values to the desired values 192
Table 6.22 Sensitivity of the model's output to variations in the inputs 193

Table 6.23 Actual and predicted mark ups of fifteen real life bidding situations 195

Table 7.1 Selection of the best structure of the neurofuzzy bid/no bid model 206
Table 7.2 Rules of rule block "RB1" 214
Table 7.3 Rules of rule block "RB2" 215
Table 7.4 Rules of rule block "RB3" 215
Table 7.5 Rules of rule block "RB4" 215
Table 7.6 Selection of the best cut-off point between "bid" and "no bid" 216
Table 7.7 Analysis of the effect of changes in the input variables on the neurofuzzy model's output 219
Table 7.8 Actual and predicted decisions of twenty unforeseen bidding situations 224
Table 7.9 Selection of the best structure of the neurofuzzy mark up model 226
Table 7.10 Rules of rule block "RB1" 230
Table 7.11 Rules of rule block "RB2" 231
Table 7.12 Rules of rule block "RB3" 231
Table 7.13 Rules of rule block "RB4" 232
Table 7.14 Sensitivity of the model output to variation in its inputs 233
Table 7.15 Actual and predicted mark ups of fifteen real life bidding situations 235

Table 8.1 Characteristics of the developed "bid/no bid" models 243
Table 8.2 Statistical measurements of the accuracy of the mark up models 244
Table 8.3 The validation indices of the mark up models 246
Table 8.4 Characteristics of the developed mark up models 247
Table 8.5 Comparison between the actual and the predicted mark up size 248
Table 8.6 Comparison between the neurofuzzy and the other mark up models 249

Table 9.1 The first five important bidding factors considered by contractors in different countries 261
Table 9.2 Advantages and disadvantages of bidding models based on different Modelling techniques 265
Table 9.3 Comparison with previous models 267

# LIST OF SYMBOLS AND ABBREVIATIONS

## Symbols

**A** An event
**A′** complement of event A
**$\alpha$** Learning coefficient
**$B_i$** Neutral score, below which a positive "bid/no bid" factor ($F_i$) will have negative effect on the "bid" recommendation.
**$B_j$** Neutral score, above which a negative "bid/no bid" factor ($F_j$) will have negative effect on the "bid" recommendation.
**B`** Adjusted neutral score
**$CA_i$** Contractor Assessment of factor $F_i$
**$CA_j$** Contractor Assessment of factor $F_j$
**$CB_i$** Contribution of a positive factor $F_i$ in the "Bid" recommendation
**$CB_j$** Contribution of a positive factor $F_j$ in the "Bid" recommendation
**H** Desired level of precision
**$Ib_j$** Importance index of Factor $F_j$ in making the bid/no bid decision
**$Im_j$** Importance index of Factor $F_j$ in making the mark up decision
**$M_j$** Mean importance level of Factor $F_j$
**$\eta$** Momentum (or membership)
**N** Total number of responses
**$N_j$** Total number of contractors who gave a score to factor $F_j$
**$NB_i$** Kill score, below which a positive "Bid/no bid" factor ($F_i$) will cause "no bid"
**$NB_j$** Kill score, above which a negative "Bid/no bid" factor ($F_j$) will cause "no bid"
**N-C-D** Normalised cumulative delta learning rule
**NT** Number of terms
**$n_{ij}$** Number of contractors who scored factor $F_j$ by $s_{ij}$
**$n_{max}$** Sample size
**n** Frequency of responses
**P** Tender price/ probability operator
**PI** Performance index
**PWD** Percentage of Wrong Decisions
**r** Pearson correlation coefficient
**R** Reduction/addition ratio
**$R^2$** Determination coefficient
**RMS** Root Mean Square error
**SI** Sensitivity Index
**Signif. T** 2-tail significance
**StD** Standard Deviation
**Si** Standard deviation of the neutral scores recommended for a positive factor Fi
**Sj** Standard deviation of the neutral scores recommended for a negative factor Fj
**$s_{ij}$** Score between 0 and 6 given factor $F_j$
**s** Estimated standard deviation in the population elements
**T** t-value statistic
**TW** Total Worth
**U1** *Theil*'s U1 statistic
**X1** A limit, above which the bidding index leads to "bid" recommendation with 100% confidence

**X2** A limit, below which the bidding index leads to "no bid" recommendation with 100% confidence

$z_q$ Normal standard deviation value corresponding to a q% confidence level in the interval estimate

## Abbreviations

**AI** Artificial Intelligence
**AHP** Analytical Hierarchy Process
**ANN** Artificial Neural Networks
**A/RT** Addition/Reduction Tender
**Ave. Dev.** Average Deviation
**BI** Bidding Index
**BOTs** Bulletin of Official Tenders
**BSUM** Bonded SUM
**CPM** Critical Path Method
**CDb** Confidence Degree in "bid"
**CDnb** Confidence Degree in "no bid"
**CoM** Centre of Maximum
**CoG** Centre of Gravity
**D-R** Delta Rule
**D-B-D** Delta Bar Delta
**DNNA** Digital Neural Network Architecture
**DoS** Degree of Support
**E** Epoch size (or Error)
**EMV** Expected Monetary Value
**ES** Expert Systems
**ExtDBD** Extended Delta Bar Delta
**Fast CoA** Fast Centre of Area
**FAM** Fuzzy Associative Memory
$\gamma$ Gamma
**IKBS** Intelligent Knowledge Based Systems
**KB** Knowledge Base
**LISP** LISt Processing
**LR** Learning rule
**Lcoef** Learning coefficient
**L** Linear
**MLP** Multi-Layer Perceptron
**MAE** Mean Absolute Error
**MAPE** Mean Absolute Percentage Error
**ME** Mean Error
**Min-Ave** Minimum-Average
**Min-Max** Minimum-Maximum
**MoM** Mean of maximum
**MBF** Membership function
**MRC** Minimum required capital for project
**NBI** Neural Bidding Index
**N-C-D** Normalised Comulative Delta
**NFBI** Neurofuzzy Bidding Index

**NET** Neurofuzzy Expert systems for competitive Tendering in civil engineering
**PROLOG** PROGramming in LOGi
**PP** Parametric Process
**POT** Price Offer Tender
**PS** Project Size
**PE** Processing Element
**QP** Quick Propagation
**SP** Syrian Pound
**TLU** Threshold logic unit transfer function
**T** t-value statistic
**TF** Transfer Function
**TanH** Hyperbolic Tangent
**$W_{ij}$** Connection weight between processing elements $PE_i$ and $PE_j$

# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

Construction contractors may secure new contracts by direct negotiation with clients or by competitive tendering (bidding). The latter method is the most commonly used in the civil engineering construction industry (Couzens *et al*, 1996; Fayek, 1996; Smith,1995; Hegazy, 1994; Shash and Abul-Hadi, 1992; Teo, 1990). Competitive tendering is essentially about making strategic decisions in respect of which contracts to bid for and the mark up level necessary to secure them (Drew and Skitmore; 1997). Under this procedure, the client invites contractors to compete for a project by tendering bids. Tenders can be seen as being made up of direct costs, on-costs, and mark up. The mark up usually contains three elements; an allowance for overheads, an allowance for risk, and allowance for profit (MaCaffer and Baldwin; 1984). It should reflect the magnitude of perceived project risks and opportunities (Bacarreza, 1973). However, different contractors may apply different mark up policies. The focus of the present work is on the process of making the "bid/no bid" and the mark up decisions. Throughout this thesis, the terms "tendering process" and "bidding process" are used interchangeably to refer to making these strategic decisions. Making the bidding decisions is a highly complex process, which involves a multiplicity of objectives and consideration of several internal and external factors (Fayek, 1996). The uncertainty, which characterises these objectives and factors, makes the bidding process even more complex. Moreover, the bidding decisions are extremely important because success and existence of any construction organisation is strongly dependent on their outcomes. Tendering decisions made on any one project have a significant effect on the short-term profit of the firm with consequent repercussions on the firm's long-term strategy and performance (Hillebrandt, 1977). Also, bidding for a new project commits the bidder to considerable bid preparation costs. For example, the cost of bidding is estimated to be 1.2 per cent of the total turnover for UK contractors (Cook, 1990). Thus, contractors have to be more selective in bidding to reduce the cost of preparing abortive bids. The absence of a suitable structured basis for dealing with this problem results often in mistakes causing loss to contractors and adversely affecting the industry. The need for automated system to assist contractors in dealing with different bidding situations has been a subject of research for a long time.

Many bidding models have been developed mainly for estimation the probability of winning a contact with a certain mark up. These models have not been popular amongst practitioners due to various reasons including the large amount of data tracking and mathematical calculations required to implement them (AbouRizk *et al* 1993). This created a need for practical and easy-to-use bidding strategies. This need is discussed in section 1.3. Whereas the following section provides a brief theoretical description of the bidding process, remaining sections are devoted to set the objectives of the present work and explain the methodology adopted to achieve these objectives. The final section presents the organisation of the thesis.

## 1.2 Theoretical Background

In the civil engineering profession, all projects have four distinct phases (Tempelman, 1982). These are planning, design, construction and operation as illustrated in Fig.1.1 Following the design phase of a project, contractors are invited to submit their bids for this project. The lowest responsible bid is usually awarded the contract for carrying out the construction activities.

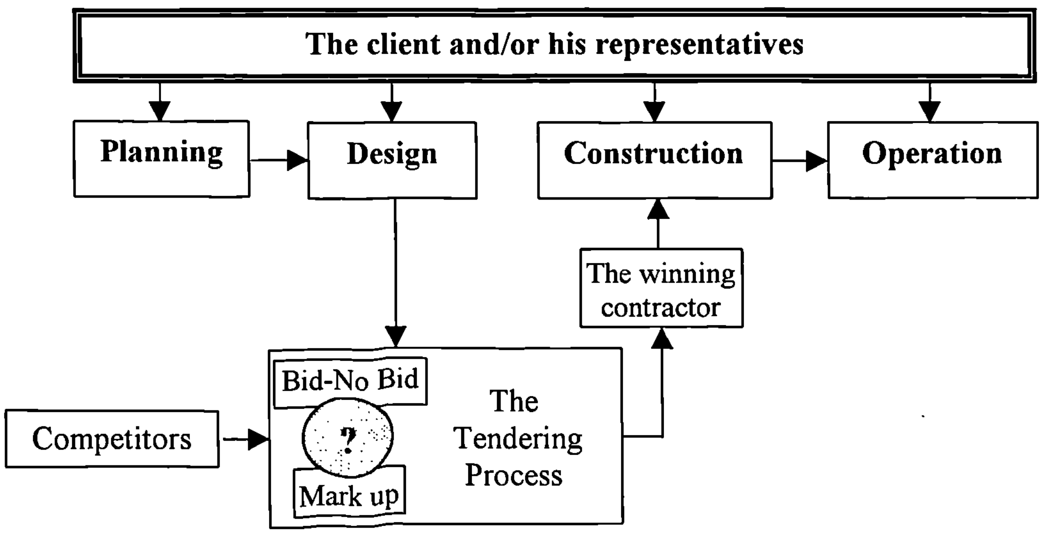



Fig. 1.1: Phases of civil engineering projects

For the contractors competing on a project, bidding is a two-stage decision making process involving "bid/no bid" and the mark up selection decisions. The possible outputs of the first stage are "submit a genuine bid", "no bid", or "submit an over-priced bid". Bidding for unsuitable projects could result in large losses or the consumption of time and resources that could be invested in more profitable projects, ultimately even financial failure of the contractor. Not bidding for a project could result in losing a good opportunity to make considerable profit, improve the contractors' strength in the industry, gain a relationship with the client, and more. Submission of an over-priced bid is sometimes made by contractors attempting not to win the contract but to maintain/establish relationships with the client and/or to keep their position in the market (Griffis, 1970). The mark up selected in the second stage of the bidding process can be defined as "the amount added to the total estimated cost of performing the project" (Bacarreza, 1973). It is usually expressed as a percentage of the total estimated cost, which includes all the direct costs (i.e. labour, equipment, materials, and subcontractors costs) plus all the indirect costs (i.e. site expenses and interest of the capital invested in the project). Estimation of the project cost is usually based on a careful analysis of possible ways of performing the project and is strongly related with the expected construction duration (Kaka and Price, 1991). Most contractors adjust productivity factors or add contingencies for the risk of each item being estimated (De Neufville and King, 1991). The product of adding the mark up to the estimated total cost is the bid price. Usually, this price must be lower than the competitors' and, at the same time, it must be high enough to guarantee the maximum possible profit or at least recover the project's cost. If the tender price was too high, the contract might not be won and, thus, losing time and money spent on preparing the tender. On the other hand, if the bid price was too low, it might not be enough to cover the actual project cost; i.e. loss. In competitive bidding, "the contractor is faced with two seemingly incompatible and contradictory objectives: he must bid high enough to make profit, yet low enough to get a job- both at the same time" (Park, 1966). Bidding situations could be classified into categories including the following:

1. The project is not desirable and/or it is beyond the contractor's capacity but a bid is submitted aiming not to win the contract but to maintain/establish good relationships with the owner and/or to keep the contractor's competitive position in the industry. The mark up in this case would be higher than usual to cover the

extra costs of procuring the unavailable required resources just in case the project has been won;

2. The project is not desirable and/or it is beyond the contractor's capacity and, therefore, a "no bid" decision is made;
3. The project is suitable but the bidder by mistake decides not to bid. That implies losing an opportunity to make some profit, gain more experience and improve the company strength in the industry;
4. The project is not suitable but the bidder by mistake decides to bid. That could result in a disaster or at least the consumption of the company's time and resources in unprofitable project; and,
5. The project is desirable, the required resources are available or could be procured/hired and the bidder decide to bid seriously for it aiming to win the contract. This is farther has many possible objectives. The ultimate objective of any construction organisation is profit. Usually all contractors try to minimise the risk of bidding less than what the project will cost. However, contractors might have other objectives such as work continuity; i.e. maintaining a certain amount of operational continuity, minimising expected losses, and minimising profits of competitors (Male, 1991).

This study is concerned with situations where either to bid on a new project as a serious attempt to win the contract or the "not to bid" decision is to be taken. If the "bid" decision was made, the final objective of bidding is making as much profit as possible. Other objectives are not directly considered. However, common sense generally provides a basis for subjective modification of profit-based strategies in order to incorporate additional criteria such as work continuity (Hegazy, 1994). Fig. 1.2 shows the decisions, the possible outcomes, and the main objectives involved in the competitive bidding process. The bold line indicates the scope of the present work. The following section discusses the urgent need for a systematic and easy-to-use strategy model to help contractors in making their bidding decisions.

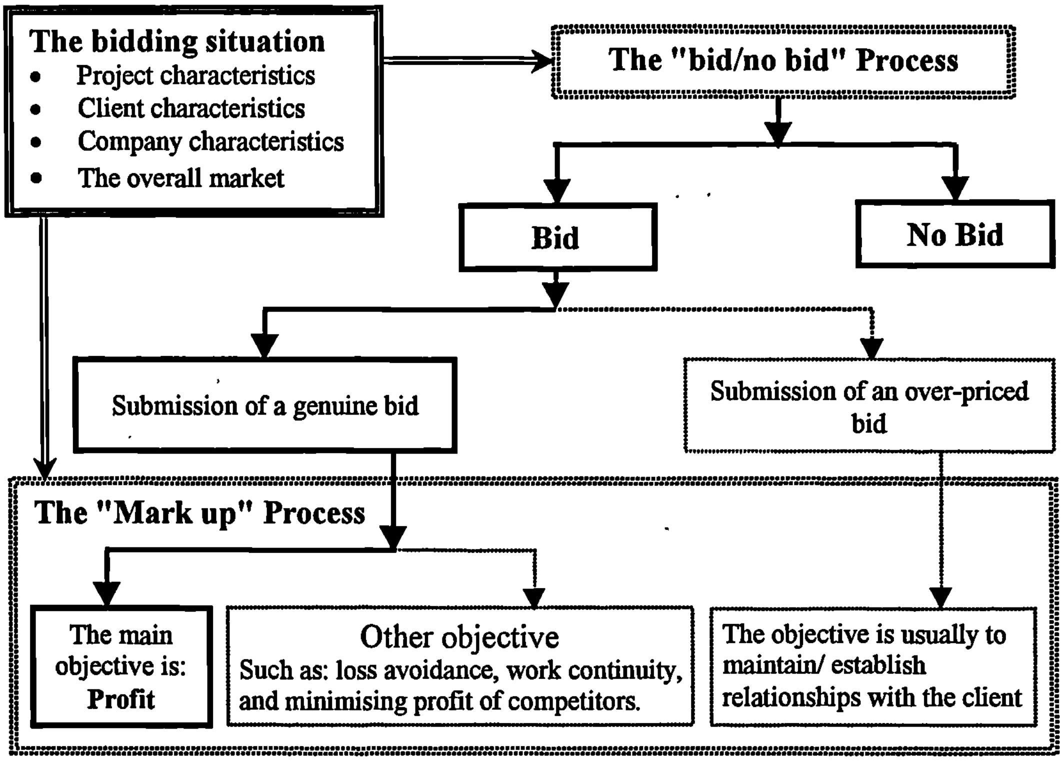



Fig. 1.2: Overview of the bidding process

### 1.3 Need for Practical Bidding Models

The civil engineering construction industry is now more competitive than ever before (Raftery, 1994). Therefore, contracts are often won on very low mark up and, sometimes, they yield negative profits (Fayek, 1996). To survive in such highly competitive industry, construction organisations should be able to successfully select suitable projects to bid on and to determine an appropriate mark up, which covers profit and unforeseen risks and, at the same time, yields a competitive bid. The usual practice is to make the "bid/no bid" and the mark up decisions on the basis of intuition derived from a mixture of gut feelings, experience and guesses (Ahmad 1990; Hegazy, 1994; Fayek, 1996). During this process, contractors need not only to consider the quantitative aspects of the cost estimate but also several qualitative internal and external aspects such as competition, risks expected, identity of the client and the overall market. Without a systematic consideration of these factors there is not any guarantee that the relevant factors are given the appropriate weight that they should receive (Bacarreza, 1973).

The inadequacy of available bidding tools have resulted in a large percentage of failures in the construction industry (Kangari and Boyer, 1988). Making the "right" bidding decisions is a very complex process. This complexity is due to many reasons including:

1. Competition;
2. Uncertainty in the estimated cost; and
3. Unpredictability of the construction difficulties (Ahmad, 1988).

Therefore, developing an effective decision-support model to help contractors in dealing with new bidding situations can yield significant benefits especially to new contractors who do not have the experience required. Nevertheless, it should be emphasised that the encouraging aspect of modelling the bidding process is not to replace the decision makers, but to be used in training exercises and to provide broad guidelines for senior management (King and Mercer, 1988). Also, mark up models help contractors to attain a reasonable degree of consistency and to check for certain mistakes. Many contractors understand that there is an urgent need to develop an appropriate bidding model to increase the effectiveness and efficiency of their bids (Teo, 1990). This need has been attracting much interest since 1956. Numerous models have been developed mainly for the mark up selection process. Most of these models have received very few practical applications in the industry. This is attributed to many reasons including:

1- The over simplicity of the assumptions of many models made them unable to represent the real world;

2- Most contractors are unwilling to struggle with sophisticated mathematical models;

3- Most available models require users to provide historical data, which are rarely available, about competitors and past projects;

4- These models are limited to small portion of the bidding situation, namely competition. They do not account for other factors such as the characteristics of the project; and,

5- Most models do not incorporate heuristic logic or subjective assessment, nor are they quick and easy to use (Wanous et al, 2000a; Dawood, 1996; Fayek, 1996; Teo, 1990; Ahmed, 1988).

Recently, many attempts have been made to capture the heuristic logic used by contractors in making the bidding decisions by applying new tools such as expert systems, neural networks, and fuzzy set theory. These attempts offer many advantages that encourage their use in the construction industry including the ability to consider the effect of multiple factors, and accepting assessments made in qualitative and subjective terms. However, these models still suffer from some disadvantages, which limit their practical applications. These include:

1- Developing models based on the traditional expert systems technique requires representing the decision-making process in terms of "if-then" rules. This is almost impossible in the bidding process because, even highly experienced contractors, are usually unable to articulate their way of thinking when making the bidding decisions. Also, some expert system bidding models account for very few factors. For example, although Ahmed (1988) has identified 31 mark up factors, he did not consider their effect in his model. Other expert systems bidding models are concerned with a certain domain. For example, the model developed by Dawood (1996) is limited to the precast concrete industry;

2- The main disadvantage of the neural network models is being unable to justify their recommendations. However, their learning power is a great solution for capturing heuristic principles used by contractors in making the bidding decisions. This can be done through real examples rather than asking contractors to explain how they make these decisions;

3- Existing bidding models based on the fuzzy set theory still require the user to perform some mathematical calculations;

4- The use of some models requires data on past projects;

5- Most models are limited to the mark up selection part of the bidding process neglecting the "bid/no bid" part; and, 6- Some of these models require large number of inputs from potential users.

Beside these limitations, the fact that different bidding conditions, and different factors are considered in different countries (Odusote and Fellows, 1992) makes it necessary to develop special bidding models for each bidding environment. As explained in the following section, The focus of the current study is the development of an innovative bidding strategy model for the Syrian construction industry, which does not suffer from the drawbacks that limit the practical applications of existing models.

## 1.4 Objectives of the Study

The main hypothesis is that, similar to other countries, the Syrian construction industry does not have a formal methodology for making the bidding decisions. Therefore, the objective of the present study is to formulise the bidding process in Syria and to develop a new strategy model, which fulfils the following criteria:

1. Potential users are not required to provide any historical data or to perform any mathematical calculations;
2. Help is provided for making both "bid/no bid" and mark up decisions;
3. Assessments of the bidding situations are made in qualitative, subjective, and approximate terms;
4. It can be easily tailored to suit individual practices of different contractors;
5. It uses explicit knowledge representation, which helps users in understanding the model behaviour.

This objective is primarily achieved by the development of an innovative neurofuzzy expert system for competitive tendering in civil engineering. The research also attempts to achieve the following objectives:

1. To review the bidding literature to study the main features of the existing models and to examine the suitability of the modelling techniques used in their development;
2. To provide a brief description of decision-making tools, which have been used in the development of the existing bidding models or are used in this study. These include an innovative Parametric decision-making Process (PP), Artificial Neural Networks (ANN), regression analysis, and the neurofuzzy techniques.

3. To define the current bidding procedure followed by Syrian contractors and identify the important factors that affect their bidding decisions;
4. To investigate the applicability of the ANN, parametric methods, and the neurofuzzy technology to "bid/no bid" decision-making process;
5. To investigate the applicability of the ANN and regression analysis techniques and neurofuzzy technology on the mark up decision;
6. Comparison between the developed models and selection of the best bid/no bid and mark up models;
7. To discuss the main limitations of the developed neurofuzzy expert systems; and,
8. To suggest areas for further improvement and future research.

The methodology adopted for achieving these objectives is summarised in the following section.

## 1.5 Methodology

A critical review of the existing bidding strategy models and the main features of available decision-making tools combined with a period of practical experience in the Syrian construction industry helped the author to formulise a methodology for achieving the stated objectives. This methodology is outlined in Fig. 1.3 and can be summarised as follows:

1. From reviewing similar surveys, a formal questionnaire was developed to identify any systematic bidding methodologies being used by Syrian contractors and to uncover the important factors which characterise the construction industry in Syria. Semi-structured interviews were used mainly to explore the tendering procedures that are most commonly used in this country. Also, through the interviews and the formal questionnaire, parameters required by the parametric process for developing the "bid/no bid" decision were identified.
2. The questionnaire findings were analysed and validated against previous research and the most important bidding factors considered by Syrian contractors were identified;

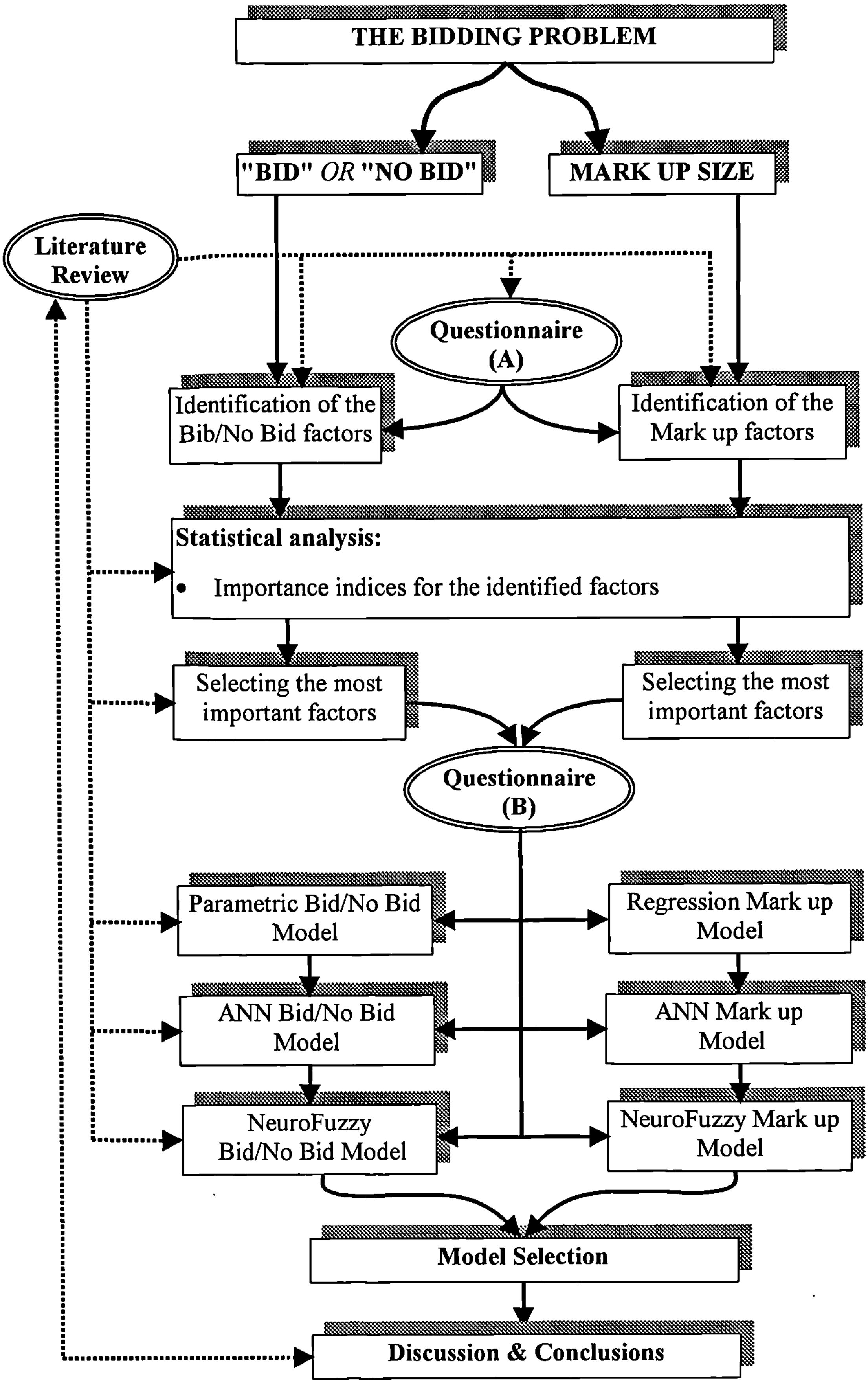



Fig. 1.3: Outline of the research methodology

3. A simple standard form (questionnaire B) was designed considering the selected important factors. Using this form, data on real life bidding examples was elicited from contractors in a situation-and-actual-decisions format.
4. Some projects were selected randomly and reserved for the validation process. The correlation between the contractors' subjective assessments of the remaining bidding examples (modelling sample) and the actual decisions made in these situations was analysed and the cause-effect relationships between the considered bidding factors and the actual decisions were studied and validated against previous research. The results of this analysis provided the basis for selecting the input factors during the development stage.
5. A innovative parametric decision-making tool was developed to model the "bid/no bid" part of the bidding process and the regression analysis techniques were used to model the mark up part. The developed models form an integrated parametric and regression bidding strategy (see chapter 5).
6. As an attempt to improve over the parametric and regression model, the ANN technique was used to model both bidding decisions (see chapter 6).
7. To achieve more improvement, another bidding strategy model was developed using neurofuzzy technology (see chapter 7).
8. An extensive analysis was carried out to select the best model. Unlike usual approach, other criteria such as consistency, user-friendliness, adaptability, knowledge representations were considered in addition to the accuracy criterion when selecting the final model (see chapter 8).
9. The neurofuzzy model has the best performance compared to the other developed models. This model was combined with a simple model to produce the bid price in the required format and, then, was implemented in a user-friendly computer prototype called NET (Neurofuzzy Expert system for competitive Tendering in civil engineering).
10. The findings of the study were discussed and compared with existing bidding models. The main scientific contributions are identified and limitations were highlighted (see chapters 9 and 10).

Following these steps has led to successfully achieving the objectives of this study. The following section outlines the organisation of the thesis.

## 1.6 Outline of The Thesis

A flowchart outlining the thesis is shown in Fig. 1.4. Chapter 1 provides an introduction, theoretical background, and justification for this research, states the thesis objectives, and describes the methodology adopted to achieve them.

Chapter 2 provides a brief review of decision-making tools which have been used in developing previous bidding models or applied in the current work. These tools are probability theory, utility theory, regression analysis, multicriteria decision analysis, artificial intelligence, and fuzzy logic.

Chapter 3 presents a comprehensive review of the competitive tendering literature. Existing tendering models were classified according to their ability to help in making which bidding decisions, i.e. "bid/no bid", mark up, or both, and according to the modelling technique they employ. The main advantages and disadvantages of these models are also highlighted.

Chapter 4 provides a brief theoretical review of available data elicitation tools. It explains the design and implementation of semi-structure interviews, and formal questionnaire surveys (A and B) used to collect the data required for:

- Identification of the current bidding procedures used in Syria;
- Identification of important bidding factors considered in the Syrian construction industry;
- Selection of the parameters required for the parametric model;
- Providing real life bidding situations required for modelling and validating regression, ANN, and neurofuzzy bidding models.

Chapter 4 also explains how the collected data was analysed and validated against previous research.

Chapter 5 explains the development of a parametric and regression bidding strategy model. The parametric process was used to model the "bid/no bid" decision. The resultant model was improved using real bidding examples and then validated on other real projects reserved for this propose. Linear and non-linear regression analysis techniques were applied on the mark up decision. The sensitivity of both parametric and regression models was analysed before testing them on real projects reserved for this propose.

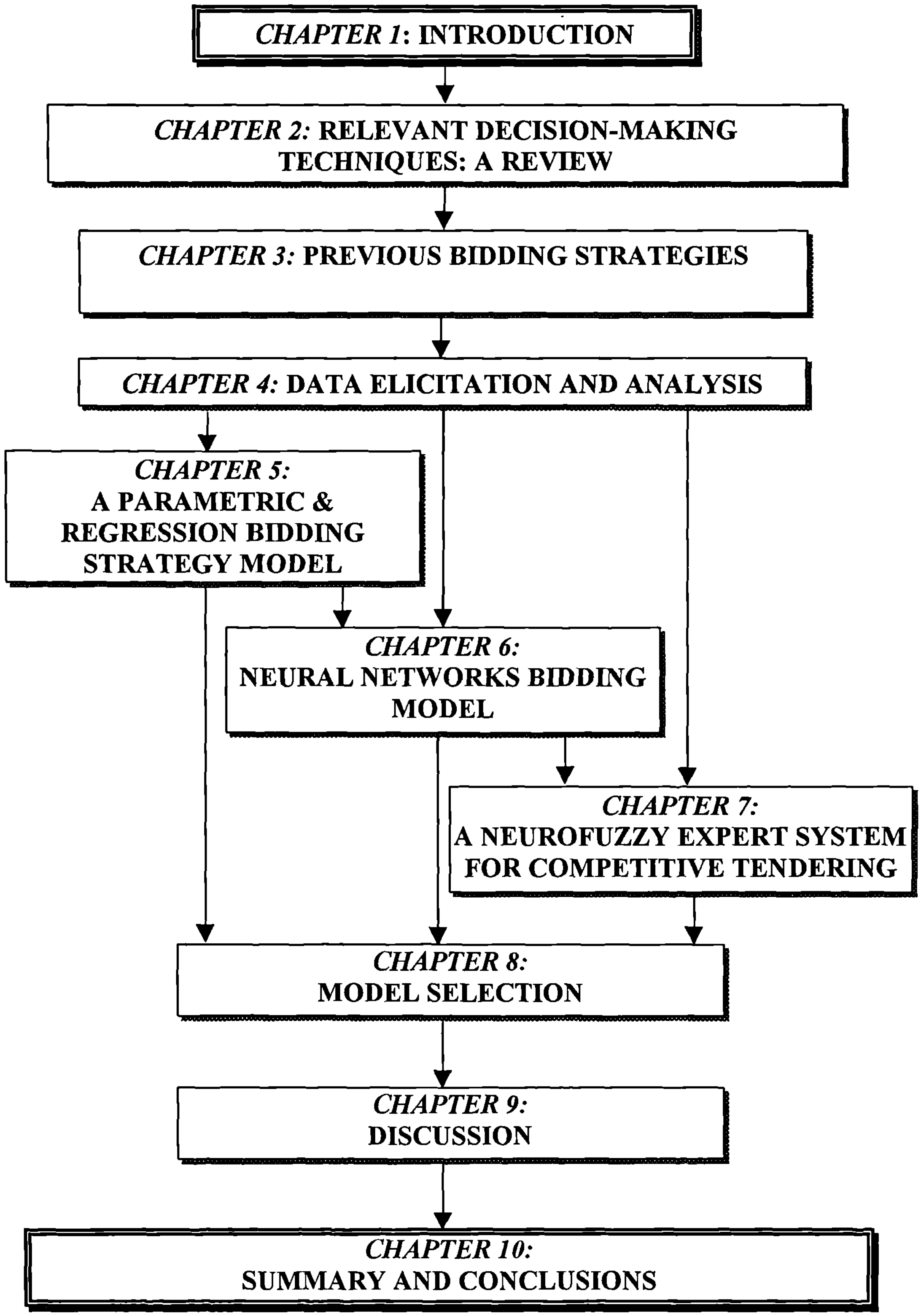



Fig. 1.4: Outline of the thesis

Chapter 6 describes the application of the ANN technique on both bidding decisions. A systematic development procedure was designed and implemented to guide this process. A simple and innovative method was developed to help in the selection of suitable input variables. Bidding situations included in the modelling sample were used for training. The sensitivity of the developed models was analysed and their accuracy was tested using unforeseen projects.

Chapter 7 introduces neurofuzzy technology as a very useful tool for modelling bidding decisions. It describes the development of a neurofuzzy expert system for competitive tendering in civil engineering. Sensitivity analysis and validation of this model are also explained in Chapter7.

Chapter 8 compares the performance and the main characteristics of the three developed models leading to the conclusion that the neurofuzzy model is the best model. Therefore, this model was selected, combined with a simple price model to produce the bid price in the required format, and implemented in a user-friendly computer prototype called NET.

Chapter 9 discusses the findings of the present study and compares them with previous research.

Chapter 10 summarises the thesis, states the main contributions, highlights limitations, and suggests new areas for further improvements and future research.

Appendix A: Questionnaire survey (A).
Appendix B: Questionnaire survey (B).
Appendix C: Non-linear regression equations.
Appendix D: Concepts used in developing the ANN bidding models.
Appendix E: Related publications.

# CHAPTER TWO
# RELEVANT DECISION-MAKING TECHNIQUES: A REVIEW

## 2.1 Introduction

Nearly every facet of life entails a sequence of decisions (Denardo, 1982). Different decisions involve different sequential activities. Nevertheless, they have some common features. Each has a purpose that interplay between constituent decisions. For instance, bidding for a new project consumes time and resources that cannot be invested in other projects. Moreover, some decisions must be made without knowing the outcomes. A contractor does not know in advance is the tender price of his competitors. If this was possible, he would adjust his price to win the contract or he might make a "no bid" decision. Uncertainty about the future lies at the heart of many decision problems. A contractor spends considerable time, effort and money preparing a bid price for a new project without knowing whether this project will be profitable or even that he/she will win the project. Nevertheless, that does not mean that the future can not be predicted. A contractor selects a mark up percentage for a new project that increases the probability of winning this project. When these probabilities can be assessed, rational decision making becomes possible (Denardo, 1982). To increase the effectiveness of the decision-making process, there must be some systematic techniques (Tempelman 1982). Hence the current chapter is devoted to provide a brief theoretical background of the decision-making methods which have been most commonly used in developing previous competitive tendering models. This could be beneficial and helpful to understand the principles of these models and to decide on which technique to be used in the present study. The reviewed techniques are classified into six main categories. These are probability theory, utility theory, regression analysis, multicriteria decision analysis, artificial intelligence and fuzzy logic techniques. These categories are explained in the following sections.

## 2.2 Basic Concepts of Probability Theory

In probability theory, an event is the term used for something, which may or may not occur. A decision problem might incorporate many events and the difficulty lies in determining the probability factor for each one of them. Usually, the probability of an event is written as:

$$P(A) = X \tag{2.1}$$

Where:

P is an operator standing for probability;

A is a symbol representing the considered event; and,

X is a number representing the likelihood of the occurrence of event A ($0 \leq X \leq 1$).

This type of probability is referred to as simple or unconditional probability because occurrences of considered events are independent from each other. The essence of the probability theory lies in the concept of complementary events. For example, when a contractor submits a bid for a certain project, he might win the contract (event A) or might not win this contract (event A'). It is always true that:

$$P(A) + P(A') = 1 \tag{2.2}$$

However, in real life situations, events do not usually occur in isolation but are strongly or weakly linked to other events (Smith et al, 1983). For example, if A was the event of getting the maximum profit and B was the event of winning a contract in a certain bidding situation, then A might very well depend on B. In such cases, A is conditional on B. This type of conditional probability is written as:

$$P(A|B) \tag{2.3}$$

The application of probability theory is based on assumptions that might not be appropriate in certain situations (Smith et al, 1983). This does not mean that this technique should not be used but merely that it should be applied carefully. The majority of traditional bidding strategy models were based on the probability theory (see section 3.2.2.1.1). Many researchers have pointed out that these models are not suitable for practitioners in the construction industry because of their unrealistic assumptions and the complexity of their mathematical operations. Therefore, some researchers have approached the bidding process using the utility theory, the basic concepts of which are explained in the following section.

## 2.3 Basic Concepts of Utility Theory

Utility is a psychological concept, which is used to measure the desire of individuals to possess units of a given commodity (Teo, 1990). It provides the basic foundation for modelling the value system of a decision-maker. This value system in the probability theory is based on the Expected Monetary Value (EMV). However, this approach has been criticised for failing to appreciate the non-linearity of the preference (value system) of individuals.

Utility is represented by curves, i.e. functions. There are three common characteristic forms of utility functions (Teo, 1990). These are risk averse, risk neutral, and risk seeking as shown in Fig. 2.1.

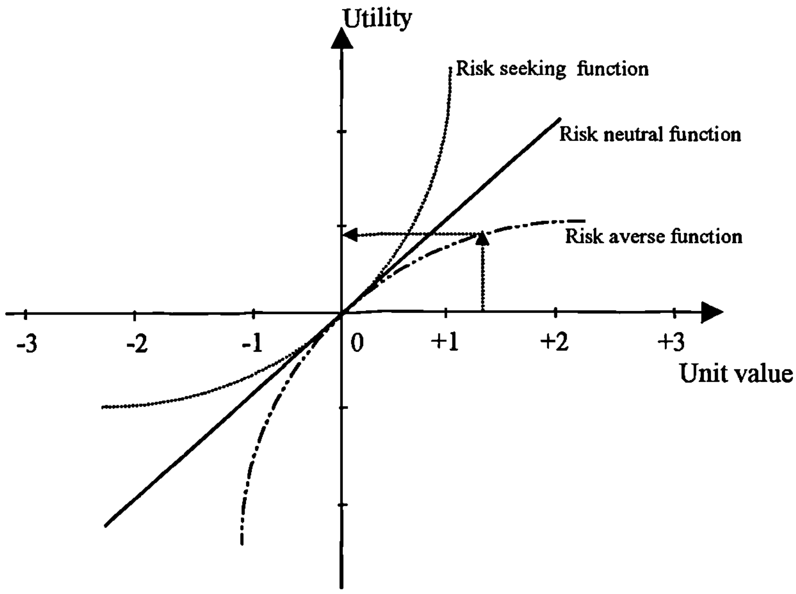
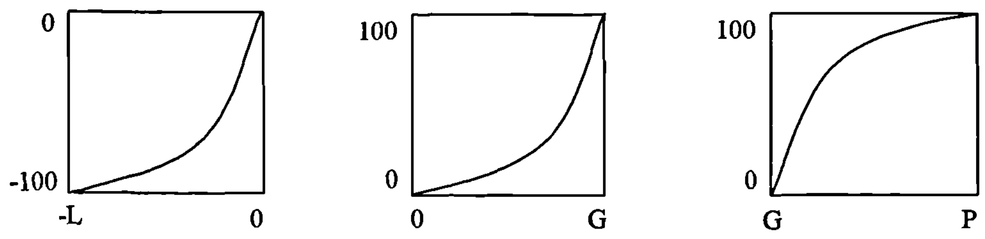



Fig. 2.1: Types of utility functions
*Source: Teo (1990)*

Once the utility function is defined, the unit value can be transformed into expected utility. Utility functions can be composed from several sub-functions. For example, Ahmad (1988, 1990) divided the mark up into three segments, loss, general overhead and profit.

Each segment, or range, was assigned a separate utility function that represents the underlying preference system of the bidder. Fig. 2.2 shows three utility functions for loss, general overhead and profit used by Ahmad (1988, 1990).




(Loss) $U_l(x)=\alpha_l+\beta_l e^{-\gamma_l x}$

(General overhead) $U_g(x)=\alpha_g+\beta_g e^{-\gamma_g x}$

(Profit) $U_p(x\text{-}g)=\alpha_p+\beta_p e^{-\gamma_p(x-G)}$

Fig. 2.2: Utility functions for loss, overhead, and profit

Where:

Ul: Utility function of loss;

Ug: Utility function of general overhead;

Up: Utility function of profit;

$\alpha$, $\beta$, $\gamma$: Constants determining the shape of the utility function.

Ahmed adopted the exponential form because it is suitable to accommodate flexibility regarding scale and shape and it can be conveniently combined with normal probability distribution function. The scale and shape of these equations are determined by range and value judgement for each one. The two extremes points of the range provide two points and the third point is assessed on the basis on subjective input by the user. This combined utility equation can be graphically represented as shown in Fig. 2.3.

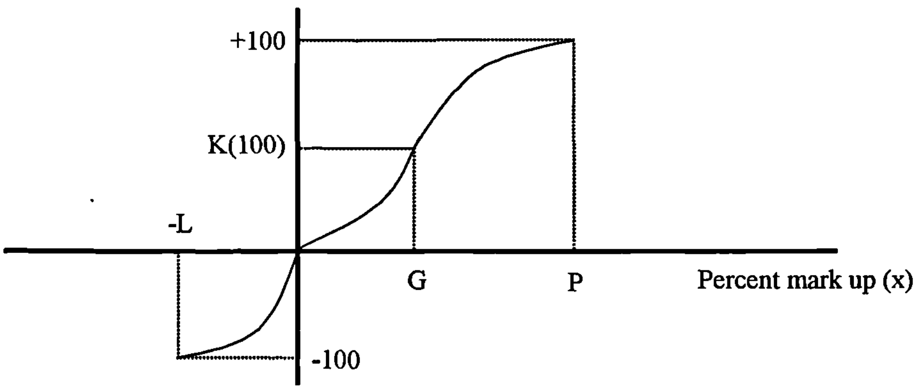



Fig. 2.3: The combined utility function.

This combined function was transformed into the final expected utility function by introducing the affect of two uncertainties; the estimated cost being not equal to the actual cost and unseen expenditures. This was done by integrating the exponential function over the probability distribution functions, which have been assumed to be normal because the actual cost is equally likely to be on either side of the estimated cost. The resultant expected utility function is illustrated graphically in Fig. 2.4, which shows how the mark up size is derived from the final utility function. The selected mark up corresponds to the maximum expected utility.

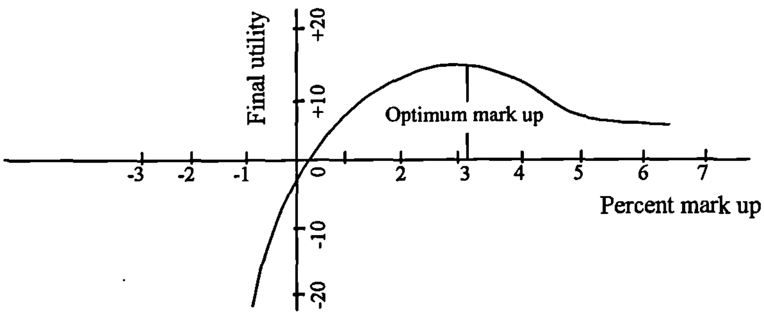



Fig 2.4: Final expected utility curve

The utility theory approach provides a better representation of the value system of the decision-maker (Teo, 1990). Furthermore, it also accounts for the risk attitude of the decision marker. Many models have been developed using this technique to systemise the mark up selection process (see section 3.2.2.1.2). However, the utility theory is still regarded by practitioners as being theoretical and mathematically complex. Additionally, it is often difficult to accurately determine the utility function of decision markers especially in highly unstructured subjective problems such as the competitive tendering process, which is liable to be affected by large number of factors. To account for the influence of such multiple factors, multi-criteria decision analysis techniques have been applied to the bidding process.

## 2.4 Multicriteria Decision Analysis Theory

Classical decision making theories deal with single criterion problems, e.g. maximising profit. But, single criterion techniques are incapable of dealing with most of the real world problems, which grow bigger in scope and complexity. Consequently, multicriteria decision making theories have evolved. The Analytical Hierarchy Process (AHP) is one of the most commonly used multicriteria technique in developing bidding models. The AHP was introduced by Saaty (1977) to compare alternatives across multiple criteria. It is based on decomposition of a decision problem into a hierarchy of criteria and alternatives. Typically, the highest level of the hierarchy is the overall goal while the next level usually consists of the decision's criteria and the lowest level generally is made up of the decision's alternatives. Fig. 2.5 illustrates this hierarchy. The decision's criteria are indicated by C-1, C-2, C-i. The alternatives are indicated by A-1, A-2, A-J.

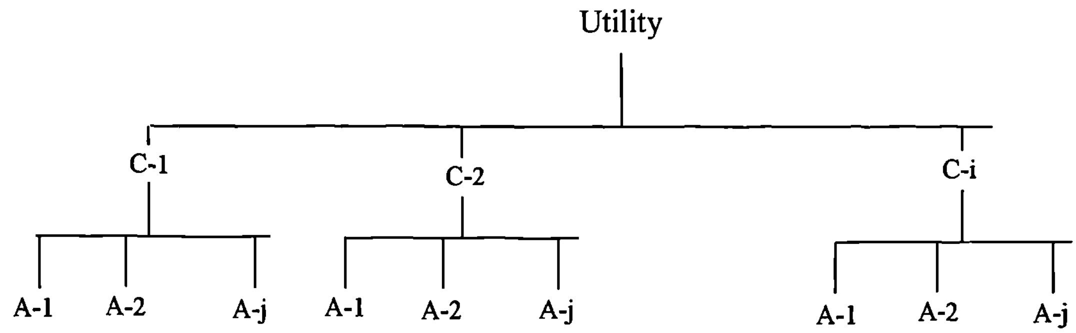



Fig. 2.5: A tree diagram for the AHP

If there are many criteria or alternatives, i.e. if any level consists of many branches, it is recommended to incorporate additional levels; i.e. sub-criteria/sub-alternatives, of the hierarchy. The relative importance is indicated at each level of the hierarchy by set of weights assigned to the criteria and alternatives. At a lower level, for every criterion, each alternative is given a weight based upon its relative contribution to the accomplishment of the final goal. The problem is, then, recomposed by multiplying the weights along each branch and summing the products for each alternative. The result is a set of multicriteria weights, one of each alternative. The alternatives are, then, ranked according to their weights and the one with the larger weight is designated as preferred. A good explanation of the AHP can be found in Bryson and Mobolurin (1994). According to Sage (1977), it is assumed that each criterion is independent in the sense that the effect of double counting is eliminated. Also, a pair of criteria is independent of a third one, i.e. the value trade-off between the criteria of this pair is not affected by a given level of a third one. Value trade-off is a measure of how much decreased satisfaction in one attribute can be achieved by increased satisfaction in another. For instance, availability of equipment owned by the contractor can be less important in the case of high availability of equipment that can be hired. Numerous researchers have used multicriteria decision making techniques to develop models for the bidding process including Ahmad (1988, 1990), Seydel and Olson (1990), and Abdelrazig (1995) (see section 3.2.1).

This technique has the ability to consider multi-attributed and subjective decisions. Thus, it can represent the bidding process more accurately than single-criterion models. Additionally, the AHP enables subjective judgements to be made regarding the relative importance of criteria and the relative weighting of alternatives, which suits the way of making the bidding decisions (Fayek, 1996). However, the AHP models require a relatively large number of inputs, i.e. weighting the decision's criteria and alternatives. Some inexperienced users might not be able to accurately provide such inputs. An innovative simple technique called the Parametric Process (PP) was developed in the present study and used as an alternative of the AHP. The application of the PP technique to develop a parametric bid/no bid model is explained in chapter 5.

## 2.5 Basics of Regression Analysis Techniques

"Regression analysis enables us to ascertain and utilise a relation between a variable of interest, called the dependent variable or response variable, and one or more independent, i.e. predictor, variable(s)" (Neter *et al,* 1979; Montgomery and Runger, 1994). Regression analysis is often used to predict the dependent variable from knowledge of the independent ones. Also, it could be used to examine the nature of the relationship between the independent variables and the dependent variable. To understand the concept of regression analysis, it is important to understand a relation between two factors. It is useful to distinguish between functional and statistical relations. A functional relation between two variable X and Y is exact; the value of Y is uniquely determined when the value of X is specified. For instance, the area Y of a square with sides X is given by the functional relation $Y = X^2$.

On the other hand, a statistical relationships between two variables X and Y is not exact. The value of Y is not uniquely determined when the value of X is specified, e.g. the relation between size and duration of a certain construction project. Fig. 2.6 shows two scatter diagrams for a simple linear statistical relation and a non-linear statistical relation between two variables X and Y.

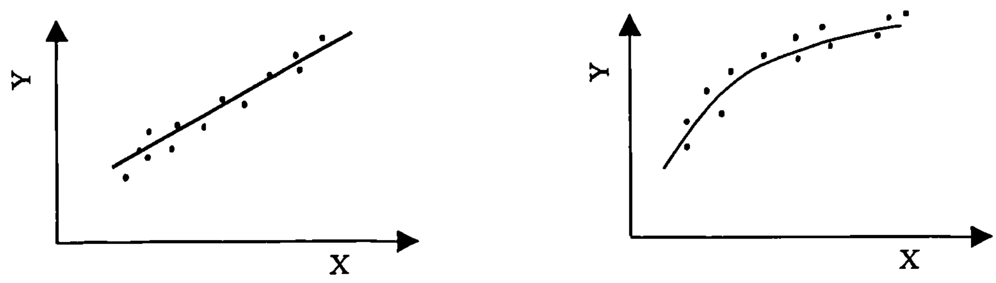



Fig. 2.6: Examples of simple linear and non-linear statistical relations

These two examples show the main features of statistical relations. These are:

1. A tendency of the dependent variable Y to vary systematically with the independent variable X; and,
2. A scattering of observations around the line or the curve of statistical relationship, partly because other factors in addition to the independent variable X affect the dependent variable Y, and partly because of inherent variability in Y.

Regression models incorporate these features of statistical relation by assuming that for each level of X, there is a probability distribution of Y. The means of these probability distributions vary in a systematic fashion with X as illustrated in Fig. 2.7.

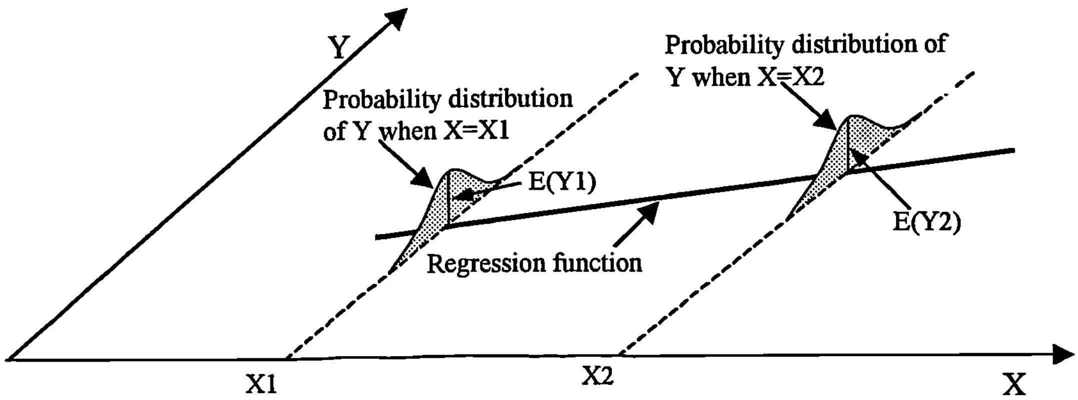



Fig. 2.7: The base of regression equations

Regression analysis techniques are classified into linear and non-linear regression techniques. Linear regression is a special case of the non-linear one. Also, there are two types of regression techniques; simple and multiple. When a linear regression equation linking two metric-scaled variables, constructed under assumption that one of the variables (Y) is dependent on the other independent variable (X), the equation is a simple regression. Such equation takes the following form:

$$Y = a + b * X. \tag{2.3}$$

Where (a) and (b) are constants. The multiple regression involves two or more independent variables. Linear multiple regression equations take the following form:

$$Y = a + b_1*X1 + b_2*X_2+ \dots\dots\dots\dots +b_n*X_n \tag{2.4}$$

Where:

Y is assumed to be dependent on the independent variables $X_i$; and,

a, $b_i$ are constants.

The dependent variable is usually plotted along the Y- axis and an independent variable $X_i$ along the X- axis. Many straight lines could appear to fit well the relation between Y and X. One of the widely used procedures to identify the best-fitting line and the corresponding equation is called the least square approach (Jain, 1996). The least square procedure will always yield a regression equation; but how trustworthy the equation is dependent on how compact the scatter diagram is and how closely it resembles a linear trend. Considering the two scatter diagrams shown in Fig. 2.8, a least-square analysis will result the same constants for the best-fitting regression equation (Y= a+ b * X) for both of the scatter diagrams.

(I) (II)

Fig. 2.8: Trustworthy of regression equations

Intuitively, the equation will be more trustworthy for (I). One criterion used to evaluate the goodness of a regression equation is called the coefficient of determination ($R^2$) where:

$R^2$ = variance explained by the regression equation divided by the total variance as shown in the following equation:

$$R^2 = SS_R/SS_T \tag{2.4}$$

Where:
$R^2$ represents the proportion of variation in the dependent variable accounted for by the independent variable(s) in the equation;
$SS_R$ is the total sum of squares that are explained by the regression equation; and,
$SS_T$ is the total sum of squared deviation of each actual value of the dependent variable (Y) from its average ($\overline{Y}$). It is computed by the following formula:

$$SS_T = \sum(Y_i - \overline{Y})^2 \qquad (2.5)$$

Also,
$SS_T = SS_R + SS_E$
Where $SS_E$ is the total sum of squares that is left unexplained by the regression equation. $R^2$ could take any value between 0, the equation does not explain any relationship between dependent and independent variable(s), and 1, perfect regression equation. The square root of $R^2$ is called multiple correlation coefficient (r), which measures the overall association between Y and $X_i$ in a regression equation.
Regressing analysis is widely used in marketing research (Jain, 1996). Also, it proved to be useful in many areas of construction management. For example, in the prediction of project duration (Chan and Kumaraswamy, 1999) and the estimation of the mark up size for new bids (see section 3.2.2.2). The main disadvantage of the linear regression technique is being unable to account for the non-linearity that might exist in the relationship between the dependent variable and the independent variable(s). Non-linear regression attempts to model such relationships. But, it needs intervention from the user. The equations should be entered manually. Therefore, it is liable to be affected by the user's bias. However, regression analysis is still more suitable for developing practical and easy-to-use models compared to the probability and utility techniques. Thus, the application of both multiple linear and non-linear regression techniques was considered in the present study.

## 2.6 Artificial Intelligence Techniques

Artificial Intelligence (AI) emerged in the 1950s and 1960s as an overlap of computer science and psychology, and concerned itself with expressing the way human mind works through the medium of the computer. It covers such diverse areas as recognising and understanding language, recognising pictures and sounds, and robotics. Two of the most prominent approaches to AI are the "symbol manipulating" and the "connectionist" approaches. Expert systems, which are more correctly called Intelligent Knowledge Based Systems (IKBS), and the artificial neural networks have emerged from the symbolic and the connectionist approaches respectively as the most widely used and commercially successful applications of the AI (Nikolopoulos, 1997). The following subsections provide a brief review of these techniques and highlight their applications in construction.

### 2.6.1 Expert Systems

Expert systems (ESs) are one of the first commercial successes of AI. They are able to solve knowledge-intensive problems that are not easily addressed by conventional software. Numerous definitions have been proposed for the expert systems. The British computer society special interest group in expert systems (Alvey) has defined an expert system as follows:
"An expert system is regarded as the embodiment within the computer to a knowledge-based component from an expert skill in such a form that the system can offer intelligent advice or take an intelligent decision about a processing function.
A desirable characteristic, which many would consider fundamental, is the capability of the system, on demand, to justify its own line of reasoning in a manner directly intelligible to the enquirer. The style adopted to attain these characteristics is rule-based programming" (Forsyth, 1984). Waterman (1986) has defined expert systems as "sophisticated computer programs that manipulate knowledge to solve problems". Recently, Jackson (1999) defined an expert system as "a computer programme that represents and reasons with knowledge of some specialist subject with a view to solving problems or giving advice". The knowledge of an expert system consists of facts and heuristics, i.e. rules of thumb. The facts constitute a body of information that is widely shared, publicly available, and generally agreed upon by experts in the field. A computer program is not given the label of an expert system just because of its ability to perform like an expert in a domain. It is more the characteristics of a system that define the system as belonging in the class of expert systems than simply

its performance (Nikolopoulos, 1997; Harmon and King, 1985). These characteristics include the system architecture, the encoding of knowledge in a knowledge base, and the availability of explanation facilities. Expert systems derive solutions based on heuristics rather than the algorithmic approach of conventional programs (Jackson, 1999; Waterman, 1986). An expert system solves problems in a narrow domain of expertise and can not be a general problem solver. Nevertheless, even in highly restricted domains, expert systems usually need large amounts of knowledge to arrive at a performance comparable to that of human experts in the field.

### 2.6.1.1 Components of an Expert System

A variety of techniques are used to create expert systems. They differ as widely as the programmers who develop them and the problems they are designed to solve. However, the principal components of most expert systems are a knowledge base, an inference engine (mechanism), a user interface, and an explanation facility (Waterman, 1986) as illustrated in Fig. 2.9.

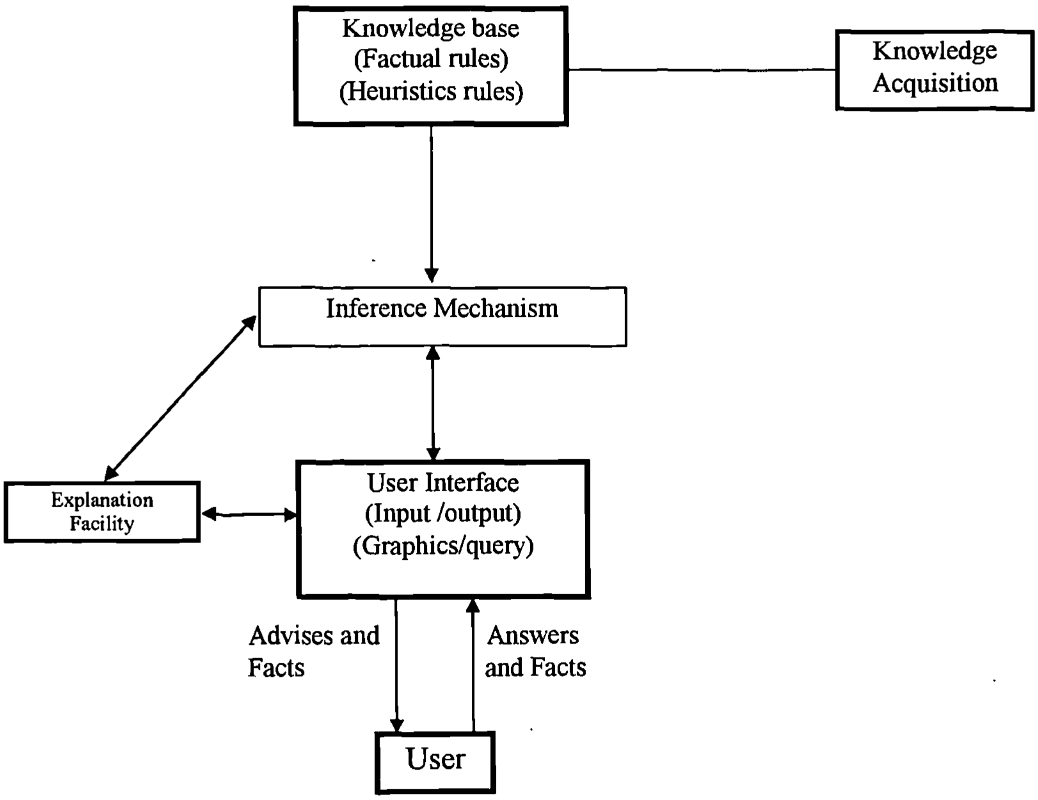



Fig. 2.9: The architecture of an expert system

### 2.6.1.1.1 Knowledge Base

The Knowledge Base (KB) is the most important part of an expert system. The validity and accuracy of system's conclusions are highly dependent on the quality of its knowledge base. The KB contains general information as well as heuristics and judgmental knowledge about the domain considered by the system. This knowledge is usually represented in the form of IF (condition)-THEN (action) rules. For example, to model the process of mark up selection, the following rules can be used:

- Rule 1: IF competition is high THEN mark up is low
- Rule 2: IF high risks are expected THEN mark up is high

Rules can be more complex in a way that two conditions are considered in one rule using AND/OR. For example:

- IF required capital is available AND required materials are available THEN Bid
- IF required capital is not available OR required materials are not available THEN No Bid

The process of collecting the knowledge base from experts is called knowledge acquisition or knowledge elicitation (Hart, 1986).

### 2.6.1.1.2 Inference Mechanism

The inference mechanism is also known as the reasoning mechanism, knowledge manager, control structure, or interpreter. This part is responsible for manipulating the knowledge base, i. e. search the knowledge base for a proper conclusion. It is usually kept in separation from the KB and is highly dependent on the development tool. In consultation with the user, the inference engine performs two major tasks; it examines existing facts and rules, and decides the order in which inferences are made. Two methods can be used to search and examine the knowledge rules. These are:

- Forward chaining (data driven). In this case, the KB is approached without knowing anything about the final goal. Facts are matched against the appropriate rule(s) and if all conditions of a rule are satisfied then that rule's action is fired. Problem data is matched against the conditions of all the available rules. Starting from the first rules, the inference engine finds all applicable ones, selects the rule(s) to be fired and then takes the action dictated by the consequence of the fired rule(s).

- Backward chaining (gaol driven). The chaining process starts by assuming some goal(s) is/are true and examines the conditions that satisfy these goals. The "Then" parts of the rules are examined to see which ones have consequences that correspond to the assumed goals. For these rules, the conditions are examined to see what facts are required to enable these rules to be fired.

The backward searching method has been applied in expert systems specialising in diagnostic and planning fields. The forward method has been used in systems in fields such as data analysis, design, and diagnosis (Efrain, 1990).

#### 2.6.1.1.3 User Interface

Facts about a current problem are usually fed into the system through dialogues with the user. The user interface allows the user to interact with the system. It may include natural language questions, menus, multiple windows, icons or graphics.

#### 2.6.1.1.4 Explanation Facility

An explanation of the system actions is usually contained in the rules that are fired. As a minimum, the explanation module should be capable of repeating the last rule. Then if the user required additional explanation the module would successively list previous rules, which were evaluated. The ability of an expert system to explain its recommendations is the most important advantage of expert systems over other approaches including neural networks, which operate as a black box (Nikolopoulos, 1997).

Other components of an expert system include a help facility, a debugging facility, knowledge acquisition module, and knowledge base editors.

### 2.6.1.2 Expert Systems Development

The tools available for building expert systems can be classified into expert systems shells and programming environments. A shell is an expert system stripped of its knowledge base. It usually contains:

1. A set of knowledge representation structures;
2. An Inference engine;
3. Knowledge acquisition tools to help the knowledge engineer in the knowledge elicitation process;
4. A user interface and explanation facility; and,
5. Interface with other software systems such as spreadsheets, databases, and programming languages (Nikolopoulos, 1997).

There are many expert system shells commercially available. These include LEUNARDO, 1st CLASS, and EXSYS. The application of shells has significantly reduced the time and computational ability needed to develop new expert systems (Efrain, 1990). But, this is often at the expense of flexibility. This can result in trying to fit the problem to the shell, rather than customising the systems to fit the problem. However, the majority of available expert systems have been developed using commercial expert systems shells (Stylianou et al, 1992). Programming environments give the developer greater flexibility. But, they require greater expertise and may be more time consuming. Expert systems have been developed using procedural languages, e.g. C or Pascal, general AI languages, e.g. LISP and PROLOG, and specialised production systems languages such as CLIPS (Giarratano and Riley, 1986). LISP (LISt Processing) and PROLOG (PROgramming in LOGic) are the must important languages in artificial intelligence fields. Using a programming language, production rules as well as the inference engine should be conceived in the language format, which are usually very difficult to write or understand by non-professional programmers. However, systems developed using AI languages are usually tailored for requirements of the domain area and characterised by flexibility and maintainability. On the other hand, the complexity of the language and the difficulty of writing complex programmes by non-professional programmers make this approach rather unfavourable.

### 2.6.1.3 Advantages and Disadvantages of Expert Systems

Advantages of expert system technology include the ability to solve complex problems, for which algorithmic solutions are not available. The driving need for expert systems is to capture critical and scarce human expertise. One highly desirable feature of expert systems is the ability to provide explanation for their recommendations. Also, they have other advantages including cost saving, efficiency, and consistency of decision making.

On the other hand, expert systems have some disadvantages. They lack the ability to learn by themselves to adopt to changing environments. Also, they are not very effective when only incomplete data is available. More importantly, building the knowledge base of an expert system is a very challenging and time-consuming task. To perform this task, experts in the considered domain should be available and welling to collaborate with the system developer. Their knowledge should be constructed in if-then format. Therefore, expert systems are not suitable for modelling complex and highly unstructured decisions where domain experts are unable to explain their reasoning process when making these decisions.

### 2.6.1.5 Expert Systems Applications in Construction

The best known application of expert systems has been in the area of medical diagnosis, where computer programs have achieved high levels of performance (Gaschnig, 1982). However, ESs have been applied to other areas including the construction industry (Ashley and Levitt, 1987; Alwood, 1989; Adeli, 1988; Anderson and Gaarslev, 1996; Mohan, 1990). Applications of expert systems in construction include:

1. Planing (e.g. Boussabaine, 1991; Ayman, 1991; Lam et al, 1993; Hendrickson et al, 1987);
2. Construction (e.g. Ahmed, 1993);
3. Contractual dispute (e.g. Diekmann, 1990; Al-Shawi and Hope, 1989);
4. Site investigation (e.g. Oliphant et al, 1996);
5. Equipment selection (e.g. Alkass and Harris, 1988);

6. Monitoring (e.g. McGartland and Kruppenbacher, 1984); and,
7. Risk management (e.g. Kangari and Boyer, 1987).

Also, a number of researchers have used ESs to model competitive tendering decisions (Tavakoli and Utomo, 1989; Phythian and King, 1992; and others) (see section 3.2.2.3).

### 2.6.2 Artificial Neural Networks

The human brain is the most complex biological system with powerful capability of thinking, remembering and problem solving known to man (Fu, 1994). This unique capability inspired research in Artificial Intelligence (AI) to model the human brain as a computing paradigm known as the Artificial Neural Networks (ANN). The key idea is to make computers learn through examples, as human learn through experience, to recognise patterns that exist within a given data set. This distinguishes ANN from other AI techniques such as the expert systems, which relay on a set of rules extracted from human experts. The main component of an ANN is called node or Processing Element (PE), which is referred to sometimes as neuron after the biological neuron. PEs in a neural network are interconnected by weighted links (synapses). Each PE can receive simultaneously many inputs. These inputs are usually multiplied by the connection weights. The PE sums the weighted inputs and transforms the product into a response, which can be an input to the following PE(s) or may be the final output as shown in Fig. 2.10.

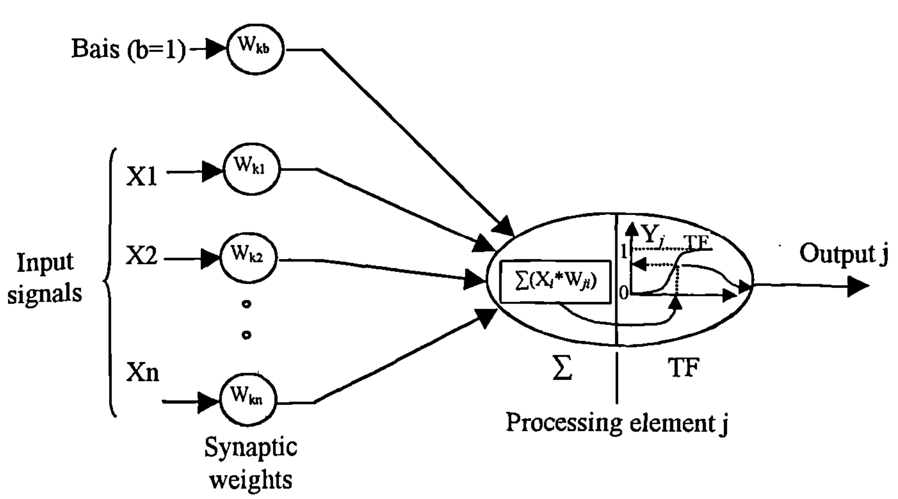



Fig. 2.10: A functional model of a processing element

The inputs of a PE also include an externally applied bias (b). The bias has the effect of increasing or lowering the response of the PE. The transformation process is controlled by a function called the Transfer Function (TF) or, sometimes, the activation function. The TF can be a threshold or a smooth function. Fig. 2.11 shows three examples of TFs.

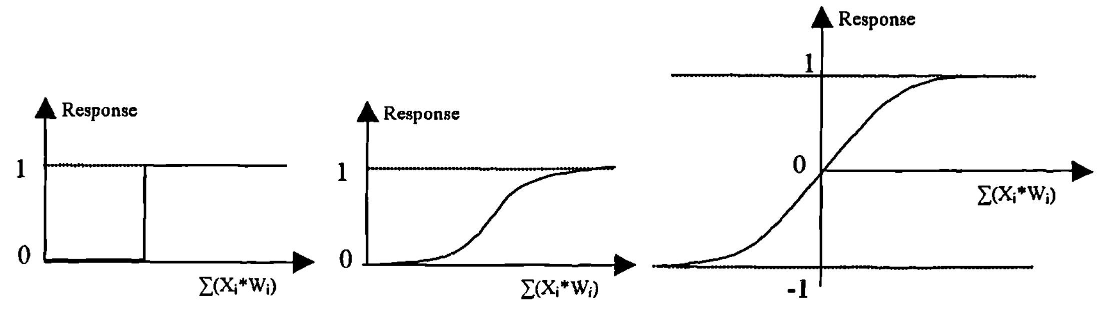



Fig. 2.11: Different types of transfer functions

The Sigmoid trenasfer function is defined in the following formula:

$$f(x)=\frac{1}{1+\exp(-x)} \qquad (2.1)$$

The Hyperbolic Tangent TF is defined as:

$$f(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \qquad (2.2)$$

The structure of an ANN model is another important aspect. There are many possible structures that can be used in modelling a certain problem. The most commonly used one is the Multi-Layer Perceptron (MLP). This type of ANN paradigm consists of an input layer (buffer), hidden layer(s), and one output layer. The PEs in the input buffer do not perform any computational tasks. They only receive the user's inputs and forward them to the first hidden layer. PEs in a neural network are connected fully or partially in a way that the output, i.e. response, of a PE is fed via the weighted connections as inputs to the PE(s) in the subsequent layer. Fig. 2.12 shows a simple fully connected multi-layered perceptron that consists of an input buffer of four PEs, a bias node, one hidden layer containing two PEs, and an output layer with one PE. The connection weights of a neural network are modified by learning from examples.

The most commonly used learning algorithm is called error back-propagation. Back-propagation algorithm was developed by Rumelhart et al. (1986). The development of this learning method played a major role in the advancement of neural networks as tools for solving a wide variety of problems (Fausett, 1994; Haykin, 1999). The flow of mathematical operations of the back-propagation algorithm using the delta learning rule is explained in Appendix D.

The following section provides a brief review of the ANN applications in the construction industry.

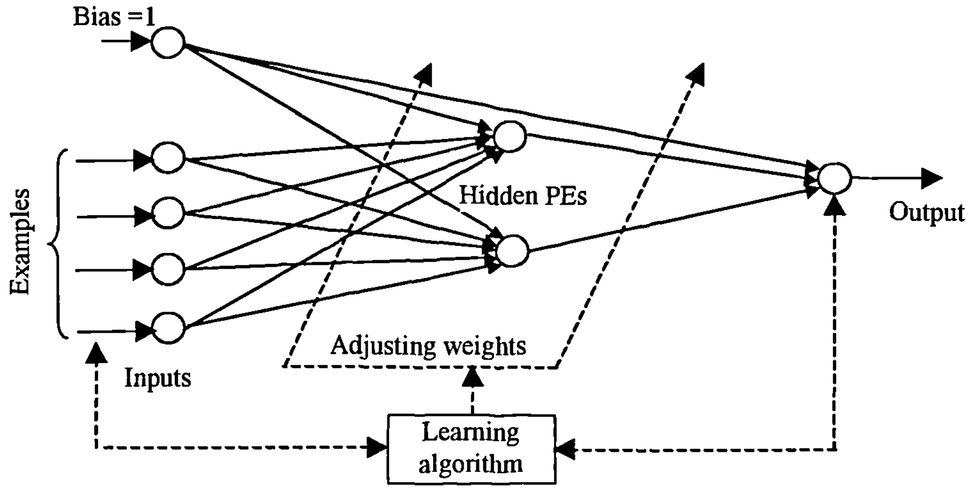



Fig. 2.12: The general structure of a multi-layer perceptron

### 2.6.2.1 Applications of ANN in Construction

ANN is a versatile tool that is readily applied to a number of diverse problems (Freeman and Skapura, 1991). Besides other applications, ANN technique is widely applied in the construction industry. "The parallel and distributed structure of neural networks along with their capabilities of generalisation, fault tolerance, adaptive and associative performance, ability to perform dynamic and real-time functions, and their limited requirements of software ensure their appropriateness for many practical applications in construction" (Moselhi et al, 1991). Many researchers (Moselhi et al, 1991; Flood and Kartam, 1994a, 1994b; Boussabainne, 1996; Andersen and Gaarslev, 1996) have highlighted potential applications of the ANN technology in the construction industry. These include prediction of project cash flow, risk analysis, resource optimistion, cost estimation, planing and scheduling, and mark up estimation. Akinsola et al (1996) developed a neural network model for prediction of the potential magnitude of variations in pricing building projects at the pre-contract stage. Many models were developed for forecasting the cost-flow of construction projects using neural networks (Boussabaine et al, 1999; Boussabaine and Kaka, 1998). Testing these models on real case studies proved that neural networks are more reliable compared to traditional methods, which are usually based on linear regression analysis techniques. Prediction of the project duration is another area in construction, on which the ANN technique has been applied (Boussabaine and Kaka, 1996; Bhokha and Ogunlana, 1999). Numerous ANN models have been developed for mark up estimation (see section 3.2.2.3). It can be concluded that ANNs are useful tools for modelling many decisions in the construction industry. "They have established themselves as an interdisciplinary subject with deep roots in the neurosciences, psychology, mathematics, the physical sciences, and engineering" (Haykin, 1999). The following section discusses the suitability of ESs and ANNs techniques for modelling the bidding decisions.

## 2.7 Expert Systems vs Neural networks

On one hand, ESs attempt to model the intelligent reasoning and the problem-solving capabilities of the human brain. Where as, ANNs attempt to model the brain learning, thinking, storage, and retrieval of information (Mosilhi and Hegazy, 1991). The major task in developing ESs is the knowledge acquisition and knowledge structuring. ESs lack the ability to learn by themselves, generalise solutions, and adequately respond to highly correlated, noisy, incomplete or previously unseen data (Pao, 1989). Moreover, the serial architecture of expert systems restricts their practicality. Further, they require intensive software development and maintenance in addition to large allocation memory (Moselhi and Hegazy, 1991). However, the selection of AI methods is dependent on the structure of the problem in hand and on the nature of the available data. ESs are suitable for problems where:

1. Deduction is involved;
2. Substantial body of knowledge connecting situations to actions is available and can be structured as if-then rules; and,
3. Experts are available and can explain why and how a certain action is made in certain situations.

But, expert systems are not suitable for other problems where:

1. Large number of interrelated factors that need to be considered in parallel;
2. Experts might not be available and/or they are unable to explain why and how they make certain decision;
3. Decisions are usually made by analogy with past experience; and,
4. Only incomplete data is available.

Neural networks are more suitable for such problems, which are so prevalent in all levels of construction engineering and management tasks. Making the bidding decisions is one of these tasks because many internal and external interrelated factors need to be considered in parallel, contractors make their bidding decisions based on analogy with past experience in a subconscious manner (Ahmad, 1990; Mosilhi and Hegazy, 1991) and they might not be able to explain how they make such decisions, and because the bidding problem is highly unstructured and can not be adequately represented in if-then rules.

Examples of past bidding situations may be the best knowledge that can be available for modelling the process of making the bidding decisions. Therefore, the ANN technology might be a better solution for this process. Many researchers including Hegazy (1994), Moselhi et al (1993) and Li (1996) have argued that ANNs technology is an effective tool for modelling the mark up decision. ANNs might be suitable for modelling the "bid/no bid" part of the bidding process as well. This will be investigated in the present work (see chapter 6). Another approach was recently adopted by researchers for modelling the mark up decision in competitive tendering. This approach is based on the fuzzy set theory, the basic principles of which are explained in the following section.

## 2.8 Basic Concepts of Fuzzy Set Theory

Fuzzy set theory is a generalisation of the conventional set theory. The concept of this theory was first introduced by Zadeh (1965). It is characterised by its membership function, which represents numerically the degree to which an element belongs to a set. Unlike conventional crisp set theory where elements are either in or out of a set, fuzzy set theory allows objects to have partial membership in a set. A membership value ranges between one (full membership) and zero (no membership).

Fuzzy set theory can be used as a method of dealing with the imprecision of the real world. Although fuzzy theory deals with imprecise information, it is based on sound quantitative mathematical theory (Chen and Hwang, 1992). It provides a suitable method of analysing complex systems and decision processes when the pattern of indeterminacy is due to inherent variability or vagueness rather than randomness (Zadeh, 1994). "Much of the decision-making in the real world takes place in an environment, in which the goals, the constraints and the consequences of possible actions are not known precisely" (Bollman and Zadeh, 1970). Decision-makers usually assign linguistic values of fuzzy nature to their forecast or description of events. Fuzzy concepts can help in making reliable decisions with ambiguous and imprecise events or facts by representing them in linguistic terms. This imprecision or fuzziness is the core of fuzzy logic. The following sections provide a brief review of fuzzy logic. This will help in understanding the fuzzy logic systems developed in chapter 8.

### 2.8.1 What is fuzzy Logic?

Fuzzy logic is a technology that translates natural language of decision policies into an algorithm (Boussabaine and Wanous, 2000). The main components of a fuzzy logic system are input linguistic variables, a rule base consisting of sets of "if-then" rules, and output linguistic variables. Each fuzzy rule has a weight called degree of support (DoS) representing its relative importance. Fig. 2.13 shows the general structure of a fuzzy logic system. The mathematical model, which enables the use of natural language by fuzzy technology to make decisions, consists of three major sections as illustrated in Fig 2.14. These are fuzzification, fuzzy logic inference, and defuzzification.

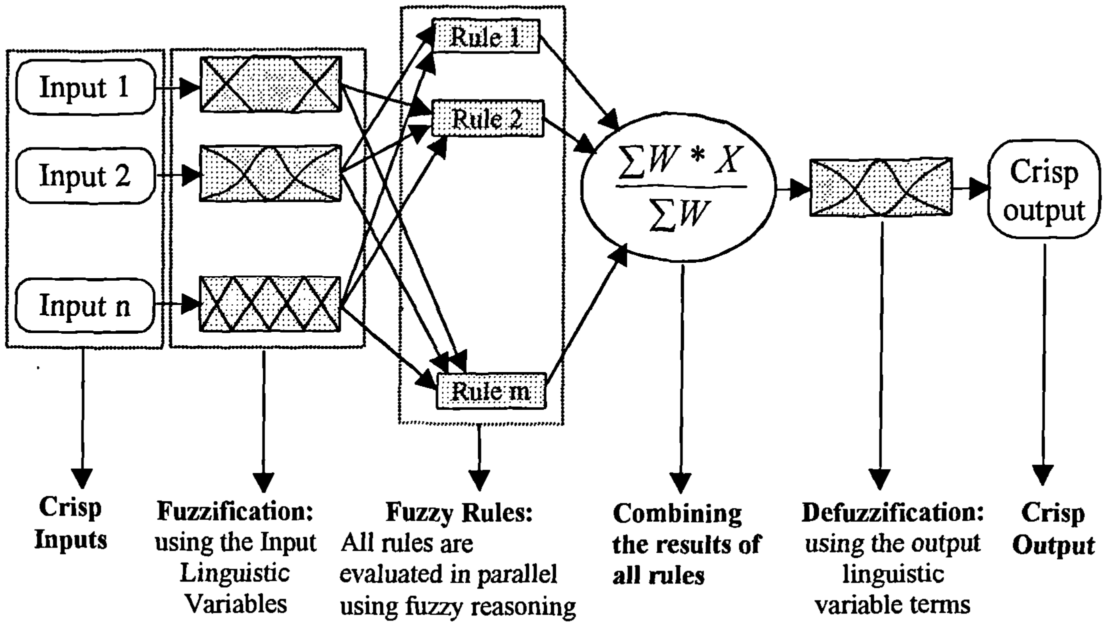



Fig. 2.13: Architecture of a fuzzy logic system

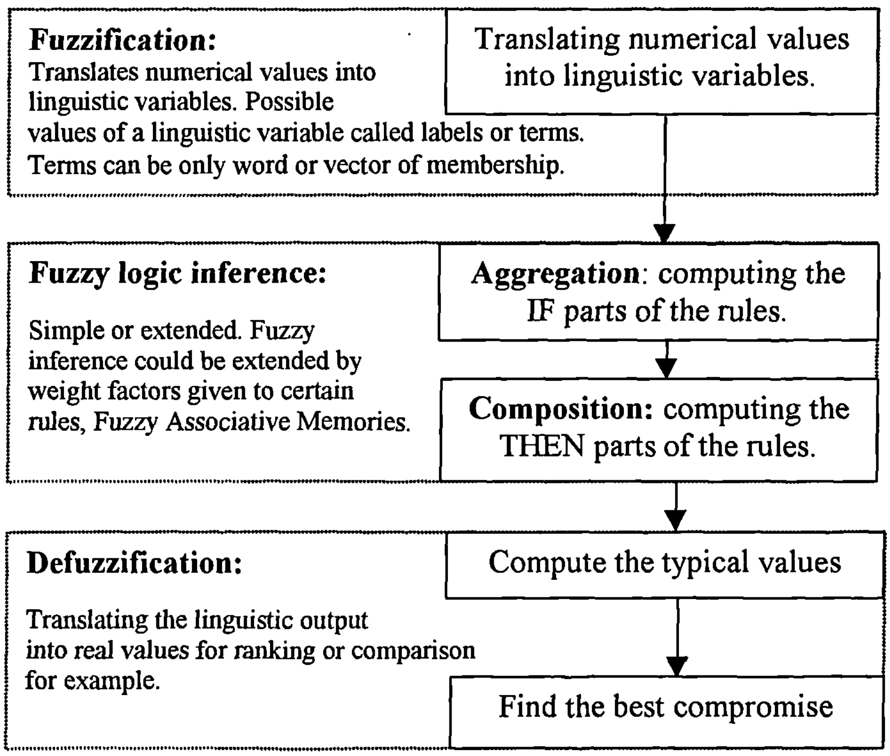



Fig. 2.14: Fuzzy logic algorithm

### 2.8.1.1 Fuzzification

All variables used in the "if-then" rules have to be defined using linguistic variables, which are fuzzy sets. Linguistic variables are the vocabulary of a fuzzy logic system. Rules that express a certain decision-making policy draw conclusions from this vocabulary. Hence, they most closely represent the way humans evaluate numerical figures (Altrock, 1997). Possible values of a linguistic variable are called terms or labels, which are fuzzy subsets. The degree to which a numerical value satisfies a linguistic variable is called the degree of membership ($\eta$). For a continuous variable, this degree is expressed by a function called the Membership Function (MBF). A great variety of membership functions have been proposed in the scientific literature. However, for input variables, the cubic interpolative S-shaped standard, i.e. maximum is always ($\eta$=1) and minimum is ($\eta$=0), MBFs provide more accurate models of human concepts for complex decision-support applications as suggested by psychological studies showing that membership functions should correspond to the following axioms:

1. $\mu(x)$ is continuous over X, i.e. small change in the input must not result in a step in its evaluation;
2. $d[\mu(x)]$ is continuous over X, i.e. small change in the input must not result in a step in its evaluation rate;
3. $d^2[\mu(x)]$ is continuous over X. This is necessary for satisfying 4; and,
4. $\mu(x)=\min_{\mu}\{\max_X\{ d^2[\mu(x)) ]/ d[\mu(x)] \}$for all X, the change in slope should be minimal (Altrock, 1996; Boussabaine, 1998; and Boussabaine & Wanous, 2000).

Where $\mu$ is the membership degree, $\mu(x)$ is the membership function, and X is the universe of the base variable, i.e. the described technical figure. For output variable, most applications use only $\Lambda$-type of MBFs (Altrock, 1997). Each term for every linguistic variable is defined by its membership function. Most of the fuzzy logic applications use between three, five, or seven terms for each linguistic variable. This is because most concepts in human language consider at least two extremes and a middle point between them. Using more than seven terms is very rare because the human cognitive capabilities are generally limited to dealing with no more that seven concepts simultaneously (Saaty 1977). As a practical approach to determining the number of terms, the design of a fuzzy logic system can be started by defining three terms for each input linguistic variable and five for each output variable. These are the minimum number of terms in most applications (Altrock, 1997). During the optimisation process, new terms can be added if required.

### 2.8.1.2 Fuzzy Logic Inference

The fuzzy inference can identify and process the rules that apply to the current situation and compute the output linguistic variables. The computation of fuzzy inference consists of two components. These are premise aggregation and result aggregation.

#### 2.8.1.2.1 Premise Aggregation

Premise aggregation computes the "IF" part and defines the degree to which a rule is valid for the given situation. Then, this degree of validation, i.e. degree of truth, is weighted by the degree of support (DoS) of this rule. The "IF" part could be a combination of two or more conditions. The combination of two conditions (A and B) can be represented by the Boolean AND (A AND B = A⊓B), which is used in the rules of the traditional expert systems. The Boolean AND can not be used in fuzzy logic where conditions are more-or-less true. Hence, fuzzy logic has other operators to represent logical connectives such as AND, OR, and NOT. These operators introduced by Zadeh (1965) are used in the majority of today's fuzzy logic applications. They are given in the following equations:

AND: $$\eta_{A\cap B} = \min\{\eta_A ; \eta_B\} \quad (2.8)$$

OR: $$\eta_{A\cup B} = \max\{\eta_A ; \eta_B\} \quad (2.9)$$

NOT: $$\eta_{\neg A} = 1 - \eta_A \quad (2.10)$$

Fig. 2.15 shows the results of the fuzzy AND, i.e. minimum, operator (plotted on the vertical axis) for any pair of membership degrees (plotted on the horizontal axes). The aggregation result is equal to one only if both membership degrees are equal to one and it is (0) for (0,0), (0,1), and (1,0). This is similar to the Boolean AND. But, the fuzzy AND (minimum operator) yields a continuous approximations for values in between, which means that the minimum operator is a continuous extension of the Boolean AND. Similarly, Fig. 2.16 shows that the maximum operator is a continuous extension of the logical OR.

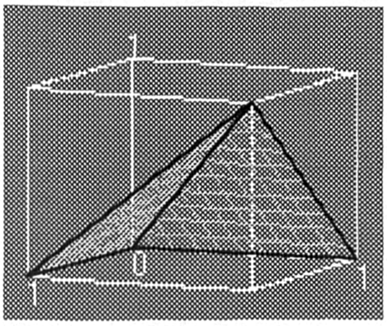



Fig. 2.15: Transfer characteristics of the Min operator

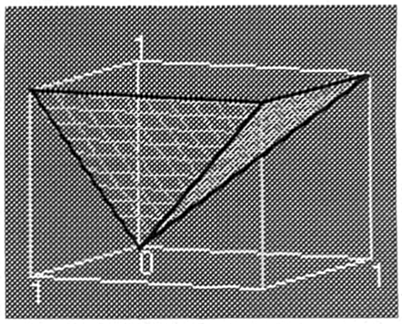



Fig. 2.16: Transfer characteristics of the Max operator

The minimum and maximum operators are most often used in practical applications because they are plausible at first glance. Nevertheless, they suffer from some limitations in the accuracy level of simulating the human evaluation process. Usually, human aggregate two criteria with the linguistic AND in a way that both criteria need to be fulfilled. However, the more both are fulfilled, the better the overall is. This implies that a low fulfillment of one criterion might be compensated by a high fulfillment of the other one. The degree of compensation is not a constant in human decision making. In stead, an entire spectrum of aggregation exists as shown in Fig. 2.17 (Altrock, 1997). Therefore, the use of a combination of the minimum and maximum operators with different degrees of compensation in fuzzy logic systems is more appropriate than using either of them. This combination is called the MinMax operator.

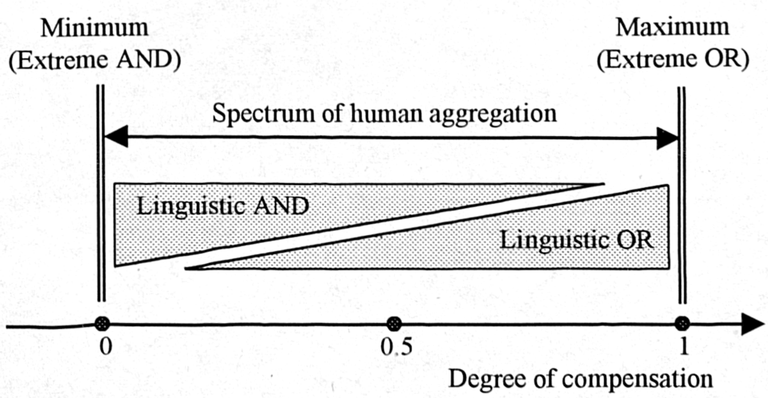



Fig. 2.17: The fuzzy logic MinMax aggregation operator

Fuzzy logic systems neither understand what implied with human statements nor can they abstractly ask for more information based on their intuition. Therefore, if aggregations other than the extreme AND and OR are used, the degree of compensation needs to be defined. The MinMax is not the only fuzzy operator available. An aggregation operator called the Gamma operator has shown more accurate representation of the human decision making process (Zimmermann and Zysno, 1983; Yager, 1992). Fig. 2.18 shows transfer characteristics of the Gamma operator with compensation parameter $\gamma = 0.3$.

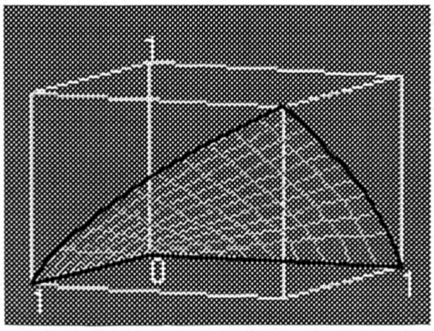



Fig. 2.18: Transfer characteristic of The Gamma operator with $\gamma = 0.3$

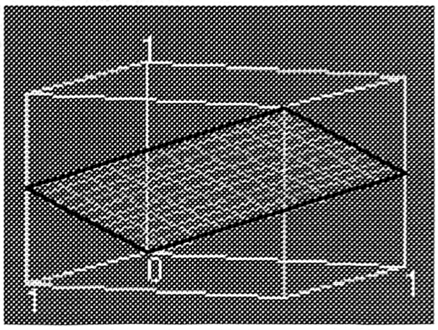



Fig. 2.19: Transfer characteristic of the MinAvg operator with degree of compensation (1), i.e. extreme AND.

Another aggregation operator that has also been applied in some applications is the MinAvg operator. It consists of a linear combination between the minimum operator and the average with a compensation parameter. This operator is faster to compute compared to the Gamma operator but it does not represent the human evaluation in the same accuracy (Zimmermann, 1987). Additionally, it is not a true extension of the Boolean AND where the four points [(0.0), (0,1), (1,0) and (1,1)] do not give the same aggregation as shown in Fig. 2.19. The aforementioned three operators are included in the used development software (*Fuzzy*TECH, 1997). There are not hard rules for determining the degree of compensation of an aggregation operator. However, experience has shown that:

- Rules that have the same input and output variables, i.e. included in the same rule block, usually have the same degree of compensation; and,
- In most practical implementations, the value lies between 0.1 and 0.4 (Altrock, 1997).

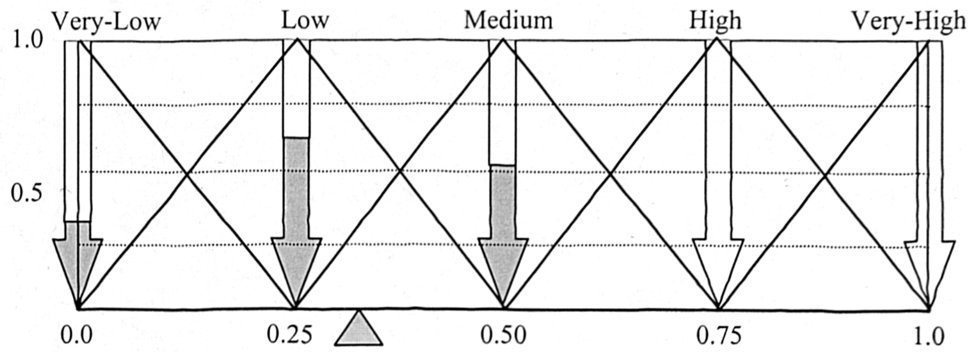
The computation of the "THEN" part of the fuzzy rules is concerned with the Result Aggregation, which is explained in the following section.

#### 2.8.1.2.2 Result Aggregation

Result aggregation (i.e. Composition) computes the THEN parts of the fuzzy rules. Each rule defines the evaluation result for a certain case in the THEN part. The degree to which the THEN part is valid for a certain case is computed by the aggregation as the degree of truth of the IF part. In the conventional expert systems, a rule could be either a member of the valid rules or not. In the fuzzy expert systems, the set of valid rules becomes a fuzzy set and, hence, allows for the definition of "more-or-less" valid rules. The most common extension to this simple fuzzy logic inference is the association of rules with weight factors, i.e. degree of support (DoS). DoSs represent the importance of the rule in relevance to the other rules in the system. The use of such weights is the most transparent implementation of more general concepts such as Fuzzy Associative Memories (FAMs). *Fuzzy*TECH supports two methods for result aggregation, the maximum method (Max) and the Bounded Sum Method (BSUM). If more than one rule has the same conclusion, the first method takes the maximum as the final result. The second one takes the bounded sum as the final result.
In some applications the linguistic output computed in this step (result aggregation or composition) is sufficient to provide a qualitative answer. In others, the numerical value of the output is required. In these cases, the following defuzzification step is required.

#### 2.8.1.3 Defuzzification

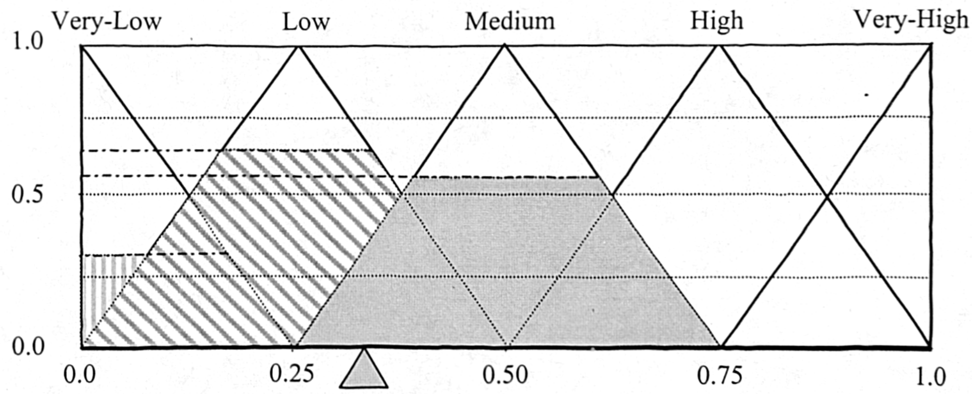
The defuzzification process (output inference) translates the linguistic outputs of the inference step into numerical values so it can be used for ranking or comparisons. The relation between linguistic values and corresponding real values is always defined using membership function definitions. Since fuzzy logic mimics the human decision_making process, a good defuzzification method should approximate to the human approach in combining fuzzy and conflicting actions. Many different defuzzification methods have been proposed and used (Ross, 1995; Kosko, 1992). One of the most commonly used methods is called the Centre of Maximum (CoM), which uses a two-step approach. First, a typical value is computed for each term in the linguistic variable as the maximum of the membership function. Second, a best compromise is determined by balancing out the results as illustrated in Fig. 2.20.




Result = 0.30

Fig. 2.20: Center of Maximum defuzzification method

Another defuzzification method that is based on the best compromise between different results is the Center-of-Area (CoA) method and sometimes it is called the Center of Gravity (CoG). The CoA first cuts the membership function at the degree of validity of the respective term as illustrated in Fig. 2.21.




Result = 0.31

Fig. 2.21: Centre of Area (CoA) defuzzification method

Then, balancing the resulting areas gives the compromising value. One disadvantage of the method is its high computational effort. The center of area is computed by numerical integration that can take up to 1000 time longer than the computation of CoM method (*fuzzy*TECH, 1997).

Therefore, an approximation of this of the CoA is more frequently used. This is called the Fast-CoA, which computes the individual areas under the membership functions during the compilation to avoid numerical integration. Also, it neglects the overlapping of the areas.

Both of the CoA and CoM deliver the best compromise result. One defuzzification method that delivers the most plausible result is the Mean of Maximum (MoM) method, which selects only the typical value of the term that is most valid. In the example shown in Fig. 2.22, the result would be (0) although the validity of V.H. term is very close to the validity of the V.L. term. This method is discontinuous because a small change in an input variable might cause completely different result. For example, small change in an input might increase the validity of the V.H. term in Fig. 2.22 to be greater than the validity of the V.L. term. In this case, the most plausible decision will jump from (0) to (1). It is often used in pattern recognition and classification applications as a plausible solution is most appropriate (Altrock, 1997).

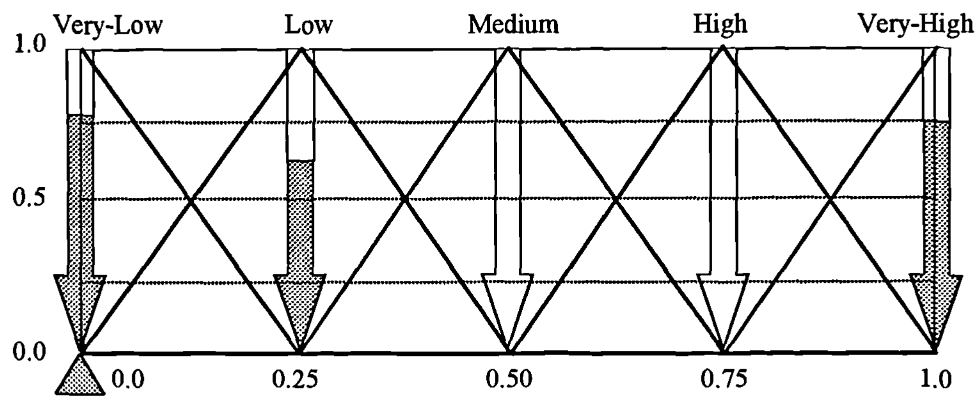



Fig. 2.22: Mean of Maximum defuzzification method

Advantages of using the fuzzy logic technology derive from its ability to:

1. Encode knowledge at very high level of abstraction;
2. Reduce the number of rules in a system; and,
3. Produce more robust and more stable systems to (Hurson et al, 1994).

To date, fuzzy expert systems are the most common use of fuzzy logic. They are used in several wide-ranging fields including financial systems, control, and data analysis. Also, there are many fuzzy logic applications in the construction industry.

### 2.8.2 Application of Fuzzy Logic in Construction

Numerous applications of fuzzy set theory exist in the construction industry including tender evaluation (Nguyen, 1985), pricing construction risk (Paek et al, 1993), construction risk management (Kangari and Boyer, 1988), analysis of project cash flow (Boussabaine and Elhag, 1999), selection of contract type (Wong and So, 1995). Fayek (1996, 1998) and Tam (1994) applied fuzzy logic approach to the process of mark up estimation (see section 3.2.2.4). As argued by Fayek and Tam, applying the fuzzy logic approach on the bidding decisions is more likely to yield a system that is more generally representative of the process of making these decisions and, hence, more widely acceptable by practitioners in the construction industry. However, despite the transparent data presentation and other advantages of fuzzy logic systems, building the rule base is a major challenge when developing a fuzzy logic model. The following section explains a solution to this limitation by combining fuzzy logic with the ANN technology.

### 2.8.3 Neurofuzzy Modelling

Neurofuzzy is a combination of ANN and fuzzy logic techniques. It provides a solution for the main drawbacks of both of these approaches. "Combining ANN systems with qualitative causal models can provide a good solution for the ANN problem of opacity" (Zadeh, 1994). Combining neural network systems with fuzzy models helps to explain their behaviour and to validate their performance. Neurofuzzy technique is a combination of the explicit knowledge representation of fuzzy logic with the learning power of neural networks. The basic idea of the composition of fuzzy and ANN methods is to achieve fuzzy reasoning by a neural network whose weights represent the parameters associated with a set of fuzzy rules. Neurofuzzy methods are purposely developed to automatically identify fuzzy rules and tune both the shapes of the membership functions and degrees of the validity of the identified rules (DoS). Neurofuzzy modelling involves the extraction of rules from a typical data set and the training of these rules to identify the strength of any pattern within the data set. The system creates membership functions from which linguistic rules can be derived as opposed to real values. Many alternative methods of integrating neural networks and fuzzy logic have been proposed in the literature (Yager, 1992). Amongst these is the Fuzzy Associate Memories (FAM) method, which is the most common approach. FAM is a fuzzy logic rule with an associated weight (DoS). This method is based on a mathematical function that maps FAMs to neurones in the neural network as illustrated in Fig. 2.23. This enables the use of a modified error back propagation algorithm with fuzzy logic. This is possible by modifying the weights of the connections of a suitable defined feed-forward ANN with a learning procedure based on the back propagation algorithm. Detailed description of the mathematical foundations of this methodology can be found in Kosko (1992) and Altrock (1995,1996). The used neurofuzzy module in the development software (fuzzyTECH) works as an intelligent assistant during the development process.

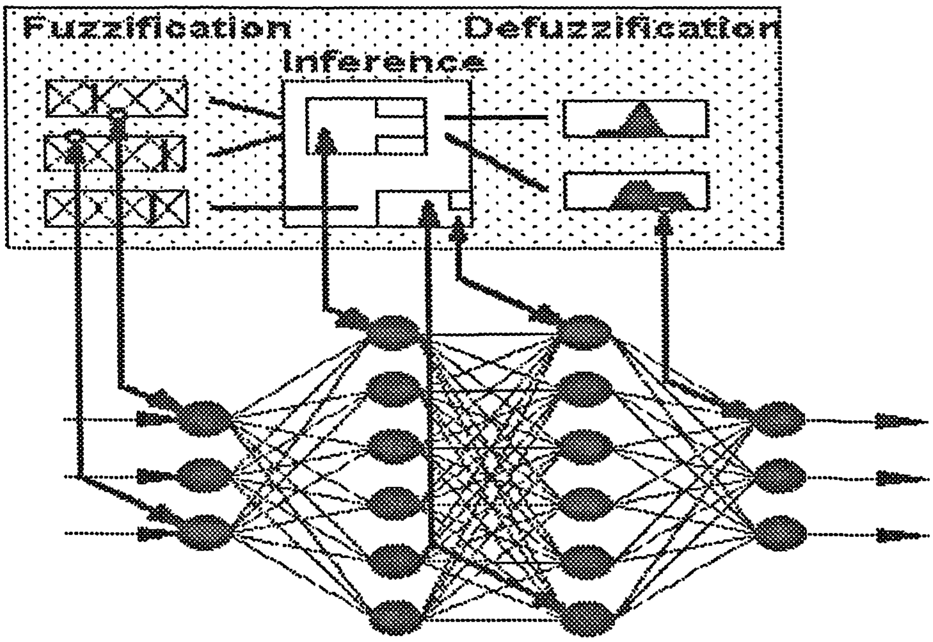



Fig. 2.23: Mapping a neural network to a fuzzy logic system
*Source: FuzzyTECH user manual (1997)*

It helps to generate and optimise membership functions and rule bases from sample data. This makes it unnecessary to worry about mathematical details of the underlining mapping algorithm. Fig. 2.24 shows the general framework of a neurofuzzy model.

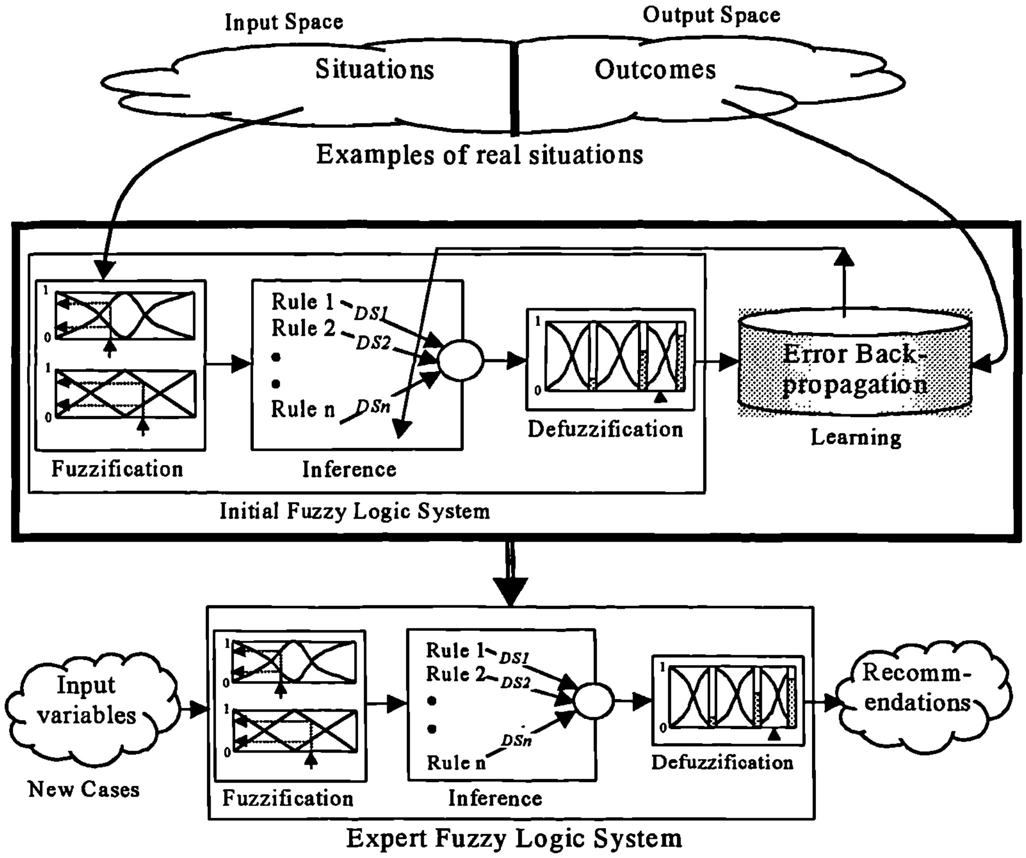



Fig. 2.24: Integrating neural networks with fuzzy logic

Neurofuzzy models are fundamentally different from neural networks and expert systems as they have the following characteristics:

1. Automatically extract the IF and THEN parts of a set of fuzzy rules from the original input/output data sets;
2. Automatically train and change the shape of member functions and the weight of the rules according to data patterns;
3. The number of neurones are determined from the number of membership functions on each input variable;
4. Training and optimisation periods are shorter;
5. Allows the inclusion of knowledge and expertise in choosing system topology;
6. The resulting fuzzy logic system is faster and more compact on most hardware platforms;
7. It is always possible to interpret the result or current stage of the system since it contains self-explained fuzzy logic rules and linguistic variables; and,
8. Leads to a model the performance of which can be directly optimised using all the available engineering know-how (Boussabaine, 1999 and Altrock, 1997).

However, there are few disadvantages of neurofuzzy compared with other adaptive techniques. These include the following:

1. There is much experience in neural networks as extensive research has gone on for more than fifty years. Neurofuzzy in contrast is still a young technology; and,
2. Neurofuzzy training features fewer degrees of freedom for the learning algorithm compared with a neural network (Altrock, 1997).

Therefore, in applications where massive amounts of data are available but no knowledge of the system's structure, Neurofuzzy may not be the best tool to be used.

### 2.9 Summary

The current chapter has provided a brief review of the main techniques that have been used in developing competitive tendering models. This review could be useful to understand the principles of the tendering models reviewed in the following chapter. Also, it provides a base for the selection of the most suitable techniques to be used in the present study. There is no point in applying the probability or the utility theories because they have been extensively used before and failed to provide a bidding strategy that is acceptable by practitioners in the construction industry. Also, the expert system technology can not be used due to the unavailability of experts who can provide the knowledge base required. Regression, decision analysis, and neural networks techniques are suitable for the multi-criteria and the subjective nature of the bidding process. They have been used other researchers with reasonable degree of success as shown in the following chapter. The characteristics of the neurofuzzy technology suggest that it could provide a very reliable tool for modelling the tendering decisions. Thus, it has been decided to apply regression, decisions analysis, neural networks, and neurofuzzy techniques on the bidding process and compare the resultant models in order to select the best one.

# CHAPTER 3
# PREVIOUS BIDDING STRATEGIES

## 3.1 Introduction

Competitive bidding (tendering) is one of the most important activities of contractors in the construction industry. This importance is indicated by the voluminous publication on bidding strategies in the literature. Numerous mathematical approaches, e.g. game and probability approaches, judgmental approaches, e.g. Delphi technique, and recently, the application of expert systems and neural networks have been developed for possible use in the construction industry. In this chapter, a comprehensive review of competitive bidding strategy models is provided. These models are classified into three categories:

- Bid/no bid models;
- Mark up models; and,
- "Bid/no bid and mark up" models.

Some categories are further subdivided into subcategories. In each category, key models are described in details to illustrate the general feature of models in this category. Other models are summarised or listed. The reviewed models are evaluated using the following criteria:

1. Considering the various factors that characterise the bidding problem in practice;
2. Ability to aid in making both "bid/no bid" and "mark up size" decisions;
3. Reliability on past data;
4. The inputs that are required from the user; and,
5. Practicality.

The limited practical application of these models and the need of the construction industry for more applicable models are highlighted.

## 3.2 Current Bidding Strategy Models

An update review of existing bidding models is reported. These models were classified into three categories; "bid/no bid" models, "mark up" models, " bid/no bid and mark up" models, and other studies. An example is provided for each category highlighting the benefits and shortcomings of these models.

### 3.2.1 "Bid/No Bid" Models

The "bid/no bid" decision is sometimes referred to as bid versus no bid decision (Ward and Chapman, 1988) or as project selection decision (Odusote and Fellows, 1992). It is a binary decision-making process, which has only two possible outcomes, i.e. "Bid" or "No Bid". But, the influences of various internal and external factors make it a very complex process. The quantification of influence of these factors is a very challenging topic. Although the "bid/no bid" decision is one of the most important decisions that have to be made by any construction organisation, it received very little attention from researchers who concentrated on the second half of the bidding process, i.e. the mark up size decision. Very few approaches that concern this decision can be found in the literature. Ahuja and Arunachalam (1984) proposed a conceptual model to aid contractors to systematically evaluate the risk due to the uncertainty of availability of the required resources before bidding on a new project. They suggested that a new project has to be examined against the following five criteria:

- Long term company goals;
- Reputation of the owner;
- Condition of the local and national economy;
- Nature of the project; and,
- Location of the project.

The project that satisfies these criteria needs an evaluation of risk due to the contractor's capacity because the project that forces hiring expensive resources may prove unprofitable. As argued by Ahuja and Arunachalam, it is vital for contractors to optimally use their owned resources by procuring new projects to employ resources that will be released progressively from ongoing projects. A CPM summery network with resources allocated to each item is required for this model that tries to help contractors balance both owned resources available from ongoing projects and resources procured. For each alternative, the model produces a duration and cost estimate for the project. In fact this model could be viewed as a resources' allocation model but not as a "bid/no bid" model. It does not have clear criteria to give a bid or no bid recommendation. The resources and risk related to them are not the only criteria that affect the "bid/no bid" decision-making process.

Ward and Chapman (1988) developed a general framework for the process of tender preparation. This framework was based on their experience on a variety of bidding situations. It considers qualitative, i.e. non-price, factors such as the contractor's assessment of his/her relationship with the client and includes an iterative process leading ultimately to the bid versus no bid decisions.

Ahmad (1990) and Ahmad and Minkarah (1990) proposed a bidding methodology based on the decision analysis technique (see section 2.4) for dealing with the "bid/no bid" problem. This model decomposes the bidding problem into four of high-level criteria and thirteen lower-level criteria as illustrated in Fig. 3.1. The required inputs are:

1. A worth assessment of each lower-level criterion;
2. A threshold worth assessment, i.e. a cat-off point between the desirable and undesirable ranges of worth; and,
3. Pairwise comparison value for each factor.

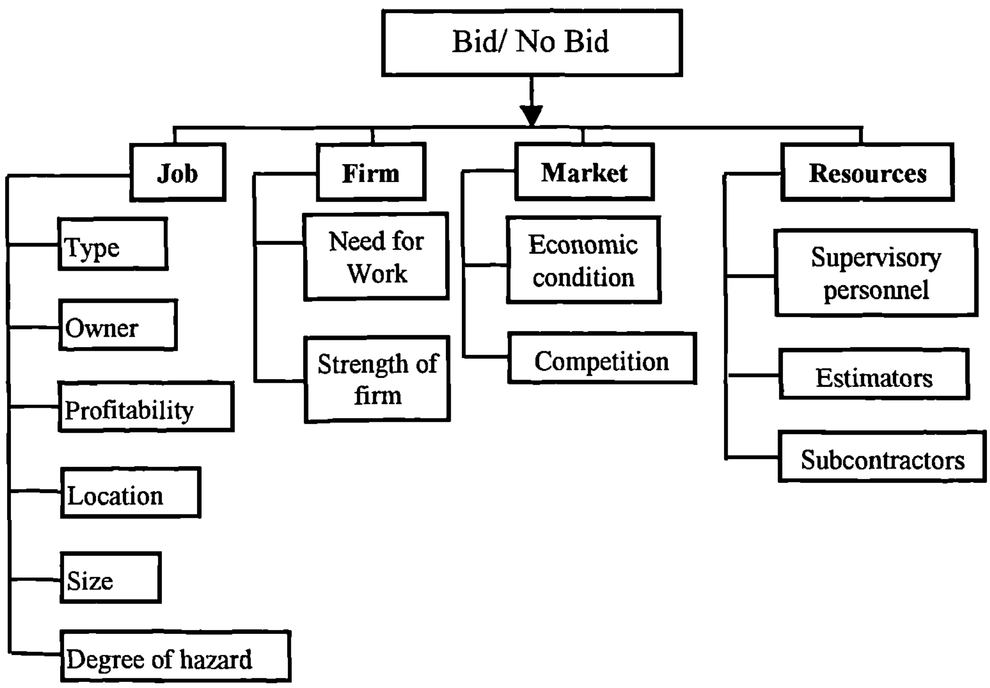



Fig. 3.1: Attributes hierarchy for "bid/no bid" decision problem
*Source: Ahmad (1990)*

This will be used to compute the normalised weights, which represent the relative importance of the factors. The following equation is used to produce the total worth of the project under consideration:

$$\text{Total worth} = W_1*S_1+W_2*S_2+ \ldots\ldots +W_n*S_n \qquad (1.1)$$

Where:

$W_i$ is a normalised worth weight denoting relative importance of the factors ($\sum W_i=1$).

$S_i$ is a worth score subjectively assigned by the contractor to each factor ($0\leq S_i\leq 100$).

Ahmad justified the additive feature of equation (1.1) by assuming that the bidding factors are independent of each other. The total worth is compared with a threshold total worth (computed in the same way using the threshold worth assessment). If the difference was positive, the "bid" will be recommended. The magnitude of the difference indicates the strength of the recommendation. This model demands many inputs, some of which the bidder might not be able to provide especially inexperienced bidders. Also, it assumes that all factors contribute positively to the total worth. No distinction was made between some factors that count for the total worth, i.e. profitability, and others that count against the total worth such as "degree of hazard". However, this approach is an important step on the road of modelling the "bid/no bid" decision.

In a case study, Phythian and King (1992) asked managers in a blue-chip engineering company specialized in the design, manufacture and commissioning of electro-mechanical products to consider various tenders and specify the factors used in discriminating between them. The managers' responses were recorded in repertory grids. Through analysing these grids, the hierarchical nature of the relationships between the key factors used by managers was extracted and, then, rules were developed. The resulting expert system could improve the consistency of making the bid/no bid decisions. However, the development of the rule base is a very complicated process and the resulting model is a company-specific system and cannot be generalized to construction projects in any way (Dawood, 1995).

Odusote and Fellows (1992) identified sixty eight factors, which were considered by one or more of a sample of seventeen authors. Some factors were omitted due to infrequent citing or because individual authors had used different expressions to refer to the same factor. The remaining forty two factors were ranked according to the number of authors who considered them being important in the project selection decision. Due to the absence of a strong agreement between authors on certain factors being important, Odusote and Fellows carried out a formal questionnaire survey supported by unstructured interviews to identify the important project selection factors considered as being important by contractors in the UK. The forty eight factors were ranked according to the percentage of the "very high" scores. The ability of the client to pay was the top important factor leading to the rejection of the hypothesis that the "resources requirements" is the most important factor, which contractors consider in making their project selection decisions. Also, the current workload is found to be important. This view is further supported by Griffis (1992) who found that "volume of work on hand is a major influence on the utility that a building contractor places on a particular bid letting".

Abdelrazig (1995) carried out a literature review and identified thirty seven factors that affect the "bid/no bid" decision in Saudi Arabia. The analytic hierarchy process was used and computer software named Expert Choice was develop to help contractors in making their "bid/no bid" decisions.

Wanous et al (1999, 2000a) proposed a new parametric approach for modelling the bid/no bid decision. The model's inputs and parameters (importance indices, neutral scores, and kill-scores) were based on the findings of a formal questionnaire survey and semi-structured interviews conducted among Syrian general contractors. All a contractor needs to use this model is his/her approximate subjective assessments of the bidding situation under consideration. The model was tested on twenty real life bidding situations and successfully simulated the actual decisions in 85% of them. The applicability of the ANN and the neurofuzzy technologies on the process of making the bid/no bid decision was first investigated by Wanous et al (2000b, 2001). The results provide evidence that these technologies are very reliable tools and can be applied to the bidding process with great confidence. The ANN and the Neurofuzzy models predicted the actual bid/no bid decisions in 90% of the same projects used to validate the parametric model (Wanous et al 1999, 2000a).

In contrary of the limited research on the bid/no bid part of the bidding process, researchers have been concentrating on the mark up estimation part of this process. The following section provides a review of the main existing mark up strategy models.

### 3.2.2 Mark up Models

Considerable research has been carried out over a period of some fifty years into the ways, in which contractors might improve their chance of choosing the best competitive mark up. Numerous models have been proposed for possible use by contractors in setting the mark up size. These models can be classified into traditional models, regression analysis models, ANN and expert systems models, and models based on fuzzy set theory.

#### 3.2.2.1 Traditional Models

The majority of available bidding models can be classified under this category. Most of these models adopted a number of distinct approaches to the competitive bidding process such as the expected monetary value, the expected utility value, and other approaches.

##### 3.2.2.1.1 Probabilistic Bidding Strategy Models

Models based on the probability theory (see section 2.2) try to mathematically express the assumed relationship between the mark up and the probability of winning the contract. Many probability-based bidding models, which have as their objective the maximisation of the expected monetary value, i.e. expected profit, have been developed. The basic theory of this approach was first developed in the USA by Friedman (1956). Freidman's model is based on the following assumptions (Ioannou, 1988):

- There is a single objective to be achieved, which is maximising the expected monetary value;
- There is an adequate supply of historical data about competitors, so that a probability distribution curve of each competitor's bid-to-cost estimate ratio can be plotted;
- Competitors do not change their bidding strategies;

- On each contract, the competitors' bids are statistically independent;
- There is no significant difference between the bidders' cost estimates. The only variation in the bid prices is due to the variation in the mark up margins; and,
- The contract is awarded to the lowest bidder.

The expected monetary value is calculated by multiplying the probability of winning the contract by the bid price minus the actual cost of completing the contract. The actual cost is the cost estimate corrected using the company's record of past estimates and actual costs. The expected profit is calculated at various bid prices. The optimum bid price is the price that maximises the expected profit.

Competitors' previous bids on all contracts for which the contractor prepared a cost estimate are used to calculate the probability of winning. A probability distribution curve of each competitor is created, which represents the probability of occurrence of different ratios of the competitor's bid to the contractor's cost estimate. Friedman's assumption of independence has created a great deal of controversy and debate (Ioannuo and Leu, 1993; Ioannuo, 1988; Binjamin and Meador, 1979; Dixie, 1974; Gates, 1979; Fuerst, 1977). However, this model is the first attempt to model the competitive bidding problem.

Gates (1967, 1971) adopted Friedman's assumptions except the statistical independence of the competitors' bids. The main difference between Gates's model and Friedman's model is the formula used to produce the probability of winning with different bid amounts. Gates proposed a formula to calculate the probability of winning as a function of the probability of winning the bid over each of the individual competitors whether or not the bids are independent.

Carr (1982) developed a bidding model similar to Friedman's and Gates's models. He adopted most of their assumptions and some new ones, which are:

- The competitors' bidding distributions are normal (less past data is required);
- Bidder have the same variance in the cost estimate;
- Variances in cost estimates are substantially greater than the margin variances;
- The magnitudes of the mark up size are not large.

Many other expected monetary value models can be found in the literature such as Sugrue (1980, 1982); Park (1966, 1979); Grinyer and Whittaker (1976); Wade and Harris (1976); Morse (1975); Oren and Williams (1975); and Bell (1969).

A number of researchers have implemented this type of mark up models in computer programmes. These researchers include Park and Chapin (1992), Shaffer and Micheau (1988), and Ward and Chapman (1988).

Many researchers have discussed the validity and practicality of the probabilistic expected monetary value models. These researchers include Fayek, (1996), Gates (1970a, 1970b, 1976), Dixie (1974), and King and Mercer (1985, 1987a, 1987b, 1988, 1990). The most important points of their debates are the models' assumptions and the necessity of historical data about the competitors.

#### 3.2.2.1.2 The Expected Utility Value Models

The objective of these models is to maximise the expected utility value. As the expected profit models, these models are based on the probability of winning a contract at a given bid price. They defer in their consideration of the uncertainty associated with the cost estimate and therefore with the expected profit for a given bid price. Benjamin (1969) proposed a utility value bidding model. This model is composed of three main parts; a probability distribution function to express the uncertainty of the cost estimate; a non-linear utility function present the contractor's preference for different amount of money; and a probability assessment of beating the lowest bidder. Benjamin presented six different probabilistic models that incorporate these three parts. The optimum bid is the maximum value of the product of the expected utility and the probability of winning. This bid is produced by trying successively large bid amounts until the maximum value is found. Benjamin adopted Broemser's (1968) regression model (see section 3.2.2.2) to predict the probability of winning a contract. Willenborck (1973) outlined a procedure to determine the utility function of a contractor, so that the contractor's risk preferences could be incorporated in a tendering strategy model. Interview technique was adopted to elicit the contractors' utility function and to identify the factors that affect the shape of this function such as the project characteristics and the economic conditions. De Neufville et al (1977) used Willenborck's approach to determine the contractors utility function. They tested this model using real data and concluded that, unsurprisingly, more bidders mean less chance of winning the contract and the economic conditions strongly affect the behaviour of contractors by affecting their decision to bid, the mark up size and the probability of winning. Ahmad and Minkarha (1987a, 1987b) developed a multi-dimentional utility theory. They defined three utility functions for the contractor's preference structure, his attitude towards loss, and the general overhead. The main advantage of this model is its ability to consider the contractor's preference structure and to handle multi-criteria decision-making problems. However, the necessity of historical data, which is usually difficult to obtain, undermines the applicability of this model to actual bidding situations. De Neufville and King (1991) modified this utility model by introducing the effect of the project risk, the owner/contractor relations, and the contractor's need for work. Griffis (1992) presented a bidding model to estimate the probability of winning a contract against key competitors about whom the contractor has past data. Griffis's model does not account for the contractor's own workload.

It can be seen that the expected utility models have some advantages over the expected monetary value models. They account for the uncertainty in the cost estimate and consider the contractor's attitude towards risks and the effect of other factors on the margin size. However, they need historical data and rely on similar assumptions regarding the independence of the competitors' bids. Also, the ill-defined utility function makes these models unpractical because of the mathematical complexity and the long time required to apply (Fayek, 1996).

#### 3.2.2.1.3 Other Approaches

Bacarreza (1973) presented a simulation model to produce the present worth of a bid at various levels of mark up. This model accounts for uncertainties affecting the present worth and thus the mark up. Other researchers modelled the mark up size decision as a simulation game including Harris and McCaffer (1989).

Gates and Scarpa (1983) used Delphi method as an attempt to develop a non-mathematical bidding model called Expert Subjective Pragmatic Estimate (ESPE) to select an optimum mark up that maximises the conditional expected value of profit based of evaluations made by a group of experts.

Farid and Boyer (1985) developed a model for the prediction of a Fair and Reasonable Mark up (FaRM) for new projects. FaRM is defined as the smallest mark up that satisfies the required rate of return of the contractor for the considered project.

#### 3.2.2.2 Regression Mark up Models

Broemser (1968) proposed two bidding models (single bid model and sequential bid model) that consider the effect of other factors besides maximising the expected profit. These factors include project size and risk of the job, amount of the job to be subcontracted, and the number of competitors. A linear regression performed on past data to produce the effect of each of these factors on the mark up. The results of the regression analysis revealed that the probability of winning is not a function of the number of competitors as assumed by the previous models. More recently, Skitmore and Patchell (1990) have suggested that the use of regression techniques might assist in modelling the bidding process and contended that there is plenty of scope for further research in the area of applying the regression analysis to help in modelling the competitive tendering process. Therefore, this technique was considered as a potential tool for developing the mark up estimation part in the present study (see section 2.5).

#### 3.2.2.3 ANN and ES Mark up Models

In the last ten years, researchers attempted to use artificial intelligence techniques to model the human decision-making process in competitive tendering. Many mark up models were developed by using neural networks and expert systems (see sections 2.6.1 and 2.6.2). ESs are based on simple heuristic rules elicited from human experts. Some researchers (Moselhi et al; 1991, 1993) argued that the application of ESs is very limited in the construction industry. They rejected the use of ESs in modelling the bidding decisions and favored the use of neural networks. The following explanations were given:

1- Problem is routine and knowledge is mainly implicit;
2- Solution is derived from a large number of highly interdependent parameters that have no precise quantification;

3- Problem area is rich in historical examples but data set is incomplete, contains errors and describes specific examples;
4- Development time of neural networks is short and sufficient training time is available; and,
5- Bid decisions, in usual practice, are based on intuition derived from a mixture of gut feeling, experience and guesses (Ahmad, 1990).

The first three arguments were, also, used by researchers who rejected mathematical bidding models in favour of ESs. Thus they cannot be considered as valid arguments for rejecting the applicability of ESs in modelling the bidding decisions. Phythian and King (1992) argued that the use of expert systems (ESs) could improve managerial effectiveness in the area of bidding because they have characteristics such as:

1. Expert systems provide a main of consolidating multi-sources of expertise within a single knowledge base;
2. Although ESs emphasise qualitative rather quantitative knowledge, they can support models incorporating both quantitative and qualitative features. Furthermore, ESs are capable of reasoning with incomplete, uncertain and inconsistent information;
3. The computerised nature of the ESs minimizes human bias, thereby insuring more objective decisions.

This is true if there is no bias in developing the rule base and selection of experts. Despite the advantages of ESs, many researchers questioned their suitability for modelling the bidding process and favoured neural networks. Unlike the expert systems, ANNs are not based on if-then rules, the construction of which is extremely hard for unstructured and highly intuitive decisions such as the mark up size. They gain their analogy-based problem-solving capabilities by learning from examples. The approach of the neural network to the mark up size estimation was developed by a group of researchers in Canada. Moselhi et al (1993) proposed a neural network decision support system for mark up estimation called (DBID). They considered the bidding factors identified by Ahamd and Minkarah (1988a) as the model inputs. Through a formal questionnaire survey, records of sixty-five real projects were collected from contractors in Canada and the United States for training the proposed system. Other seven case studies were used to test its generalisation ability. The mean absolute error was 15.11%. The DBID uses the back-propagation neural network paradigm (see section 2.6.2) and requires three sets of input data. These are:

1. Company characteristics (e.g. company size, mark up components);
2. Data about past bids (successful and unsuccessful); and,
3. Risk factors affecting the mark up size such as site conditions, inaccurate cost estimate, etc.

These inputs are entered by selecting a number on a scale ranging from one (Low) to five (High). The system's outputs are:

1. The recommended optimum mark up size;
2. The win/loss possibility;
3. The difference between the winner and the second bid ($);
4. The anticipated profitability (low, medium, high, or loss);
5. The project potential for changing orders (low, medium, or high);
6. The project potential for claims (low, medium, or high); and,
7. The anticipated duration extension as a ratio of the original duration.

The DBID is also complemented by a sensitivity analysis capability using Monte Carlo simulation technique to enable the user to perform what-if analysis such as the change in the optimum mark up as a result of the changing the assessment of certain risk factor.

Li (1996a) developed a neural networks mark up model with one input layer and one out put layer. The input layer contains five nodes for the number of bidders, need for work, company size, construction cost, and inflation rate. Some of these inputs are in numerical format, e.g. rate of inflation, and others are subjective assessments, e.g. need for work. The output layer contains one node for the recommended mark up percentage. Various numbers of hidden layers were examined. Data about one hundred and fifty-five bidding cases collected for a bidding game curried out in an undergraduate construction project course. This data was used to train the mark up model and other five cases were used to test it. Two hidden layers with eleven nodes in each one helped to get the best performance. The average error in predicting the actual mark ups of the test cases was 10%. Using the same data, Li (1996a) compared the performance of ANN and stepwise linear regression techniques. The regression model predicted mark ups for the test cases with average error greater than 10% leading to the conclusion that ANN technique is superior to regression analysis (Li, 1996a). Another comparison between these techniques was made by Andersen and Gaarslev (1996) who used data from Broemser's regression model. Unexpectedly, they concluded that their neural networks model does not produce a valuable predictions and the regression model produces better results. However neural networks offer many advantages to modelling the mark up prediction problem including (Moselhi and Hegazy, 1991; Hagazy, 1994; Li, 1996a, 1996b; Li and Love, 1998; Li et al., 1999; Boussabaine et al., 1999):

- Qualitative assessments can be used;
- The ability to learn from real life examples, which can be elicited from contractors instead of asking them to perform a highly complex task and articulate how they make the bidding decisions;
- The inputs required are not difficult to obtain and no need to extensive historical data about past projects and competitors;
- Incomplete and inconsistent data can be used in training the neural network; and,
- The ability to consider multiple criteria.

On the other hand, the neural networks have some disadvantages such as (Dawood, 1995; Fayek, 1996; Li et al., 1999):

- The data required for training is usually confidential;
- The neural net work can only replicate the decision-making process used in the training data and can not give any explanation for its outputs;
- Designing a neural network model is largely based on trial and error. Therefore, the appropriateness of its structure is questioned; and,
- Amending the structure of a neural network is not possible by a certain user to suit his/her specific strategy.

Despite these disadvantages, it seems that the ANN is still one of the most suitable tools for modelling the bidding process. Therefore, unlike previous studies, the application of this technique on both "bid/no bid" and mark up decisions is investigated in the present study (see chapter 6).

#### 3.2.2.4 Models Based on Fuzzy Set Theory

Paek, et al. (1993) reported a new approach using fuzzy set theory in the pricing of constriction risks. Tam et al. (1994) presented a fuzzy logic-based model for the estimation of an optimum mark up percentage. This model is based on a set of rules derived from factors considered in tendering as shown by the response to a questionnaire survey of contractors in Hong Kong. Fifteen mark up factors that are considered important by contractor in Hong Kong were identified. These factors are: project characteristics and risks (location, type of contract, design elements included, client, design team and consultant, duration, and project size); market conditions; current workload; political stability; changes in legislation (environmental control, safety, and technical matters); availability of labour; availability of materials; currency fluctuation; and, inflation. In this model, each factor is decomposed into a number of fuzzy subsets that defines a level at which this factor may exist. For instance, the project size has tow subsets; small or large. The subjective assessment provided by the user is used to calculate the degree to which the project is small and the degree to which the project size is large. The generated membership values are passed to the inference engine. The rule base is composed of thirty linguistic rules. Using the Maximum-Minimum composition operator (see section 2.8.1.2.2), each rule analyses the degree of membership in the fuzzy subset for each factor and recommends a margin size associated with a degree of strength. The recommendations of all these rules are, then, composed using the centre of gravity method (see section 2.8.1.2.2) to produce the final risk allowance recommendation. Although this model is specific to the Hong Kong construction industry, it illustrates how the fuzzy set theory can be used successfully to model the mark up size decision-making process. However, building the rule base is a very difficult task. Also, modelling a complex decision such as the mark up decision in thirty if-then rules can be questionable. Fayek (1996, 1998) proposed a decision support system that utilises fuzzy logic to help contractors in making the mark up decision. This system provides more than ninety factors that may affect the mark up size. Additionally, it attempts to address that contractors might have multiple objectives when making the mark up decision. These are:

1. To maximise the project's contribution to profit;
2. To test a new geographical area; and,
3. To win the project.

The user needs to specify the mark up range (minimum and maximum values) as shown in Fig. 3.2.

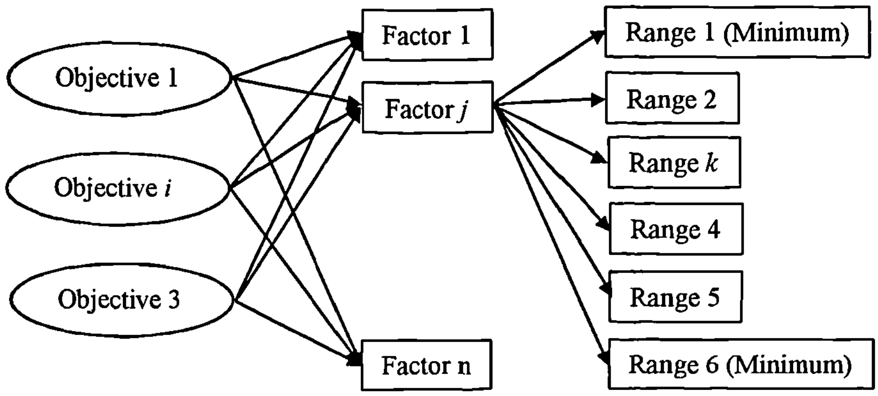



Fig. 3.2: Components of bidding strategy model (Fayek, 1996)

This range is divided equally into six sizes. Also, the following entries are required:

1. Degree to which each objective is desired (on a scale between 0 to 100);
2. Degree of applicability of each factor (on a scale between 0 to 100);
3. Degree of influence of each factor on mark up size (on a scale between 0 to 100); and,
4. The most suitable mark up that each factor would indicate in order to achieve each objective in turn, assuming that both the factor and the objective exist at full strength. This mark up is chosen as one of the sixth values generated in the mark up range.

The selected most suitable mark up is given a weighting of 1.00 in the model. Other weightings decrease by 0.20 in either direction starting from the chosen value. Then, the fuzzy binary relations are established to link the objectives and the mark up sizes sets to the factors set. The min-max composition method is used to identify the strongest relations between the objectives and the mark ups. These correspond to the degree to which a mark up size is recommended. Values of mark up are ranked according to the strength of their relations with the objectives. To get a single value, the centre of area de-fuzzyfication method (see section 2.8.1.3) is used. This model, although it has many advantages over previous models, is mathematically complex and the number of inputs is very large. For example, if a user considered only ten factors from the list provided by the model (93 factors), 55 inputs would be required. However, it demonstrates that fuzzy logic enables more general relationships to be established between data items that affect the mark up size decision (Faiyk, 1996, 1998). Using such technique is more likely to yield a system that is more generally representative of the bidding decision-making process in bidding and, hence, more widely applicable in the construction industry. Fuzzy logic allows assessments to be made in qualitative and approximate terms, which suit the subjective nature of the bidding process.

### 3.2.3 "Bid/No Bid and Mark up" Models

Very few of the available bidding strategy models can help construction contractors in making both "bid/ no bid" and mark up decisions. Ahmad and Minkarah (1988a) developed an expert systems to aid contractors in deciding whether to bid for a new project or not and in setting a suitable margin size. The commercially available expert system shell called EXSYS was used in building this model that is based on the additive utility model (Ahmad and Minkarah ,1987b).
Based on the project characteristics and a knowledge base of if-then rules, the system recommends whether to bid or not associated with a degree of confidence. If this degree is higher than a cut-off score, the system automatically proceeds to recommend a margin size for the project. The bidder inputs values for the utility function parameters to establish his/her preference structure associated with loss, overhead, and profit. The outputs of this model are:

1. Whether to bid or not with a degree of confidence;
2. A bid price;
3. The estimated cost, which is user-defined;
4. A mark up size; and,
5. The probability of winning at the suggested mark up size.

AbouRizk *et al* (1993) proposed a prototype knowledge based expert system called BidExpert that demonstrates the basic reasoning used for making bidding decisions. This model is integrated with a database management program call BidTrak, which is responsible for retrieving historical information from past bids submitted by the company and its competitors. The user is requested to provide information about the project and the company. The information provided by the user and retrieved from BidTrack is, then, passed to BidExpert.

Two external programs are linked to BidExpert; the Fair and Reasonable Mark up pricing model (FaRM) developed by Farid and Boyer (1985) and a program to calculate the estimation accuracy of the company. BidExpert processes the outcomes of these models using its knowledge base and provides the user with a "bid/no bid" recommendation. Once the "bid/no bid" decision is made, this model provides advice on the optimum mark up. The necessity of historical information undermines the wide applicability of this model. BidExpert has other drawbacks. For instance, the company capacity is evaluated by the number of projects the company has handled in the last five years and the number of the current projects without any consideration of the projects' sizes. Also, this model is more an information system than an expert system. However, it is another step on the way of automating the bidding decision-making process and it is a good tool for storing and managing historical data about previous projects (Dawood, 1995). Dawood (1995) developed an integrated bidding management expert system for possible use by the make-to-tender precast concrete companies. This system is composed of an information system that analyses the records of previous contracts and a knowledge base of rule elicited from past contracts records and from expert managers. It can help the bidding managers in assessing the suitability of incoming inquiries and suggest a "bid" or "no bid" decision and, if required, provide advice on the optimum mark up.

This model was developed for the make-to-tender precast industry only and can not be use by contractors in other construction bidding situations.

### 3.3 Summary and Conclusions

From reviewing the bidding literature, it is evident that contractors in different countries consider different bidding factors. Although there are some common factors, they do not have the same importance in all countries as has been found by previous surveys. For example, the "project size" is ranked as the first most important mark up factor in the Saudi Arabia (Abdul-Hadi, 1989; Shash and Abdul-Hadi, 1992-1993), as the third factor in the USA (Ahmed and Minkarah, 1988a), as the ninth in the UK (Shash, 1995; Shash and Abdul-Hadi, 1993), and not refereed to at all in Australia (Fayek, 1996). The results of these surveys differ due to different aims of the surveys, different bidding conditions, and different factors considered in each country (Odusote and Fellows, 1992). Therefore, a new survey is required to determine the tendering factors considered and the tendering strategy adopted in the Syrian construction industry. No similar surveys exist in the available literature. Another important conclusion can be drawn form the voluminous bidding literature. There is surprisingly little progress towards a generally agreed approach, which is realistic and useful to those making the bidding decisions. Competitive bidding models based on the probability theory and multi-criteria decision analysis techniques were the earliest models developed. Their use in the bidding practice is, however, limited due to many disadvantages. They require historical data on past projects and competitors, which are usually not available; they are based on over-simplified assumptions; they require extensive mathematical and statistical knowledge; most of them do not incorporate heuristic logic and subjective assessment, which are the basis of making the bidding decisions in practice. However, these mathematical models laid the foundation for subsequent attempts to formalise the competitive tendering process.

The artificial intelligence neural networks and expert systems techniques have been used to develop new bidding strategies that incorporate heuristic rules and accept subjective assessments as inputs. These models also improved on earlier ones as they do not require extensive mathematical knowledge, some do not require historical project or competitors data, and they are easy and quick to use. Despite these improvements, they have some drawbacks. Usually, contractors make the bidding decisions in a subconscious way. Even highly experienced contractors find it difficult to explain and articulate how they make the bidding decisions (Moselhi et al., 1991; Moselhi et al. 1993). This makes it almost impossible to elicit the knowledge rule base, which is the main block of the expert systems. Moreover, some expert systems require historical knowledge (AbouRizk et al., 1993) and others are domain-specific, e.g. Dawood (1995). Dawood's model is limited to the precast concrete industry. Also, some expert system mark up models depend on supporting models, such as the utility value models (Ahmad, 1988). Developing neural network models require historical data for training, which is not easy to obtain in the sufficient quantity and quality. The neural network models are suitable only for situations that are similar to those used for training, which makes them population-specific. Additionally, these models have been criticised of being very implicit because they do not provide any justification of their outputs.

However, the suitability of the ANN technique to the tendering process is evident as supported by many researchers (see Section 3.2.2.3). Taking this into account, it is surprising to find some studies in the literature suggesting that ANN does not produce valuable results when applied to the mark up process and regression analysis produces better results (Gaarslev; 1991; Andersen and Garrslev, 1996). Also, it has been claimed that modelling techniques based on the fuzzy set theory yield systems that are more generally representative of the decision-making process used in setting the mark up size and enable more general relationships to be established between data items that affect this decision (Fayek, 1998, 1996; Tam et al., 1994). This general disagreement on one most suitable approach to be used in modelling the tendering process calls for testing more than one approach and selecting the best one for a particular case. Nevertheless, all surveys agree that a need exists for tendering models that are based on qualitative and subjective assessments, and which (unlike the traditional probabilistic models) account for a wide range of factors in addition to competition and profitability (Fayek, 1996). Also, based on the review provided in the current chapter, it can be argued, that regression, ANN, and fuzzy logic techniques are from the most suitable techniques for modelling the competitive tendering process compared to other techniques. Therefore, it was decided to investigate the applications of regression, ANN, and a combination of ANN and fuzzy logic (neurofuzzy) techniques on the tendering decisions in Syria. After identifying the need for uncovering the factors that characterise the tendering decisions in this country, the following Chapter discusses the methodology used to collect and analyse the required data.

# CHAPTER 4
# DATA ELICITATION AND ANALYSIS

## 4-1 Introduction

A survey was carried out to provide a general review of the current bidding practice, identify the bidding factors considered in Syria and to obtain actual data for development and validation of innovative bidding models. The purpose of this chapter is to describe the data elicitation process and to report on its findings. A brief theoretical review of the available data collection techniques is provided. The current bidding practices of Syrian general contractors are identified through interviews and a formal questionnaire survey. Real life case studies are collected using a second questionnaire. An analysis of the collected data and a discussion of the results are presented.

## 4-2 Theoretical Background

Chisnal (1992) makes the distinction between public and private knowledge. Public knowledge includes the published definitions, facts, and theories of which textbooks and references in the domain of study are typically composed. But expertise usually involves more than just this knowledge. Human experts generally possess private knowledge that can not be found in the published literature. This knowledge consists largely of rules of thumb, i.e. heuristics. Heuristics enable human experts to make educated guesses when necessary and to deal with incomplete data. The collection of such knowledge from human experts is a very hard task. First, the expert must be identified, next he or she must be persuaded to assist and finally the relevant knowledge must be elicited from him or her. The last part is usually the hardest, as much of the knowledge an expert possesses is used in a subconscious manner (Hutchinson *et al*, 1987).

Bramer (1987) points out that much of the expert knowledge is of an ill-defined and heuristic nature, frequently at unconscious level. Much of the human expertise is approximate rules of thumb, which are seldom or never recorded. The methods of collecting knowledge from human experts include questionnaires and interviews. In this study, a detailed review of the literature on bidding strategies in construction was conducted. List of possible factors influencing the bidding decisions was prepared. This knowledge is not sufficient and the heuristic knowledge of human bidders is needed. Hence, the questionnaire survey and semi-structured interview techniques were used to collect the required data. The next section provides a brief review of these techniques.

### 4-3 Data Elicitation Methods

Several methods of obtaining information from the industry are available in the literature. Four possible methods of data collection were reviewed:

- Questionnaire survey;
- Interviews;
- On-site observations; and,
- Analysing documents, records and census materials (Oppenheim 1992).

The questionnaire and interview methods have been used and proved to be sufficient in similar previous studies. Therefore, they were used in the present study. These two method are explained in more details in the following two subsections.

#### 4-3-1 Questionnaire Survey

A questionnaire is simply a set of questions designed to generate the data required for accomplishing a research project' objectives. The questionnaire is the quickest and the least expensive technique for obtaining the required information (Parasuraman 1991). It involves sending a written questionnaire (through the post, the electronic mail, etc.) to potential respondents for completion and return to the researcher. According to Raj (1972), this method can be preferred over others in situations such as:

a- The potential respondents are spread all over the country;

b- Some of the required answers need some time to consult certain documents; and,

c- Some respondents are willing to answer some questions through the mail more than in face-to-face conversations.

However, questionnaire techniques have some drawbacks. The questions must be constructed in a simple and straightforward format. Also, the level of non-response can create difficulties. Response rate can drop to less than ten percent in some cases. To increase the expected response rate, the layout of the questionnaire should be attractive looking and the questions should be simple and clear. The number of questions needs to be reduced to the barest minimum. Repetitive reminder (telephone call for example) is also very helpful to enhance the response rate (Raj 1972).

The process of drawing up a questionnaire is not an easy undertaking. It is a sequence of interrelated tasks. The logical starting point is to translate the data requirements into a set of rough questions. Next, certain critical checks of this set have to be made. For instance, is each question relevant and properly worded?. Fig. 4.1 outlines the general process of designing a questionnaire as suggested by Parasuraman (1991). Numerous loops of chicks may be required before a suitable draft of the questionnaire is produced. The relevance of each question must be carefully examined and irrelevant questions must be dropped. Question wording is also a very important factor. It plays a critical role in the data accuracy. Sequencing of questions is another determinant of the data accuracy. In order to win the co-operation of more respondents, the final draft should be accompanied of a concise cover letter to inform the potential respondents what the study is all about and, more critically, to convince them of the importance of participating in it.

### 4-3-2 Interviews

An interview has been defined as: "a conversation directed to a purpose other than satisfaction in the conversation itself" (Chisnall 1992). Others defined it as "an encounter between a researcher and a respondent in which an individual is asked a series of questions relevant to the subject of the research" (Ackroyd and Hughes, 1992). Usually an interview's schedule that contains the questions to be asked is used. The respondent's answers constitute the raw material to be analysed in a later stage of the research.

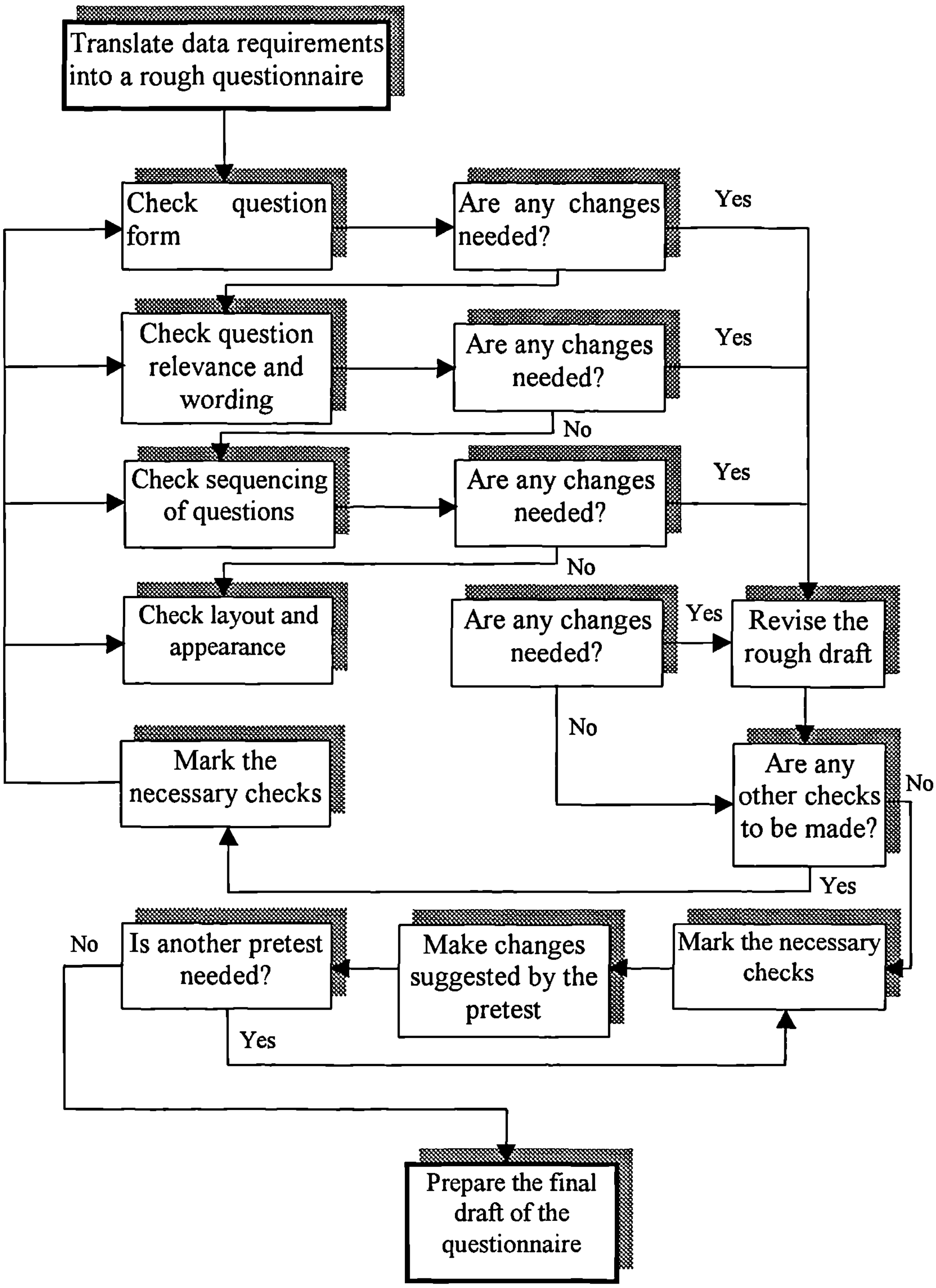



Fig. 4.1: Components of the questionnaire design process
*Resource: Parasumraman (1991)*

These answers are usually recorded and subsequently analysed along with other responses from other interviewees. The quality of the interview depends largely on the interviewer developing a relationship with the respondent, which will encourage good communication.

The distinctive role of the interviewer is concerned with securing valid information about a particular problem, which has been carefully predefined. This role can be summarised in the following four duties (Chisnall 1992):

a- Locate and contact respondents who fulfil the research's objectives;

b- The second duty of the interviewer is to translate this contact into effective interview;

c- Secure valid and reliable answers, which give information that is useful to the objective of the survey. To get such answers, the questions have to be carefully worded and presented; and

d- Recording accurately the responses given during the interviews.

Interviews can be classified into three main types in terms of their degree of standardisation (Ackroyd and Hughes, 1992):

1- Structured (or standardised) interviews in which interviewers use a schedule to which they must strictly adhere for all respondents. All respondents should be asked the same questions and in the same serial order. This is, in an effort to ensure that any variations in replies are not artefacts of variations in the way of asking the questions. This technique is less costly in time and effort to administer and more straightforward to code and process.

2- Non-structured interviews. In this type, the interviewer uses a list indicating the topics to be covered. They are free to ask questions in whatever way they think it is appropriate and natural and in the order they feel to be more effective. The flexibility is the key feature often recommended in pilot studies preliminary to a full-scale study. It is also useful where little about any systematic nature is known about the topic. There is a limit to which this type of interviews can be used with large samples. It is extremely costly in time and money and the data collected are not easy to code and analyse.

3- Semi-structured interviews. This type is between the two extremes of the structured or non-structured interviews. The interviewer is normally required to ask specific questions but is free to probe beyond them if necessary.

The semi-structured interviewing technique has some of the advantages of reliability, structure and control associated with the more structured interviews and some flexibility of response obtainable by a less structured interviewing methods (Dawood, 1995). For these reasons, this technique was used to support a formal questionnaire survey in investigating the current bidding practice in the Syrian construction industry.

### 4-4 Semi-Structured Interviews

Six semi-structured interviews were conducted among selected expert contractors. The selection criteria were being general contractor, running a successful business, with considerable experience on the Syrian construction industry and, above all, willing to be interviewed. The main objective of these interviews was to gain a general understanding of the current bidding practice in Syria. These interviews were needed to support other findings of another technique (a formal questionnaire survey), therefor the issue of representativeness has not been considered in the selection process. The contractors interviewed were prominent general contractors with (19-31) years of experience. In the beginning of each interview, contractors were introduced briefly to the study and its objectives. Thereafter, they were requested to answer certain open-ended questions regarding the following aspects:

1- The current tendering procedures adopted in Syria, the current practice of making the bidding decisions and any decision-support systems they use in this process;
2- Situations where one individual factor may be enough to cause a "no bid" decision and the identification of such factors; and
3- The mark up components.

In the end of each interview, the contractor was given a copy of the written questionnaire and requested to point out any questions that need some modifications to ensure that they are easily understandable and to add any important bidding factors that are not listed already in the questionnaire.

### 4.5 Questionnaire Surveys

Numerous questionnaires have been conducted in different countries (Ahmed and Minkarah, 1998; Odusote and Follows, 1992; Shash and Abdul-Hadi, 1992; Shash, 1993; Hegazy and Moselhi, 1995; Ting and Mills, 1996; Uher,1996; and Fayek, 1996). However, a new survey to collect the data required for the present study is necessary for the following reasons:

1- The results of these surveys differ due to different aims of the surveys, different bidding conditions, and different factors considered in each country (see section 3.3);
2- To format of the required data is different form previous studies; and
3- No previous studies are available on the Syrian construction industry.

Thus, two formal questionnaires were used for gathering the information and data required for developing and validating new bidding models for possible use in Syria. The first one, questionnaire A, was concerned mainly with uncovering the important factors that characterise the "bid/no bid" and the "mark up size" decisions in the Syrian construction industry. The second questionnaire, questionnaire B, was devoted to gathering data about bidding situations in terms of the most important factors identified from the findings of questionnaire A and the associated decisions made by the contractors in real life.

### 4-5-1 Questionnaire A

A formal questionnaire was prepared to identify the contractors' opinions about the importance of qualitative factors that affect the "bid/no bid" and the "mark up size" decisions. The design and structure of this questionnaire is outlined in the next sections.

#### 4-5-1-1 The Development of Questionnaire A

The process of designing this questionnaire survey was performed through the following steps as illustrated in Fig. 4.2:

1- Defining clear and precise objectives of the questionnaire. These objectives are:
   - To uncover some of the general features of the Syrian construction industry.
   - To identify those factors that characterise both of the bidding decisions in Syria; and

  - To develop a neutral score for each "bid/no bid" factor below/ above which it starts to discourage the "bid" recommendations.

2- Deciding what factors and questions to be included within the questionnaire to help achieving these objectives. Based on previous similar questionnaires and on the author's practical experience in the Syrian construction industry, thirty four factors were considered.

3- Selecting a suitable style for the questions included in the questionnaire. The closed style was selected where the respondent is offered some answers for each question to choose from. This makes it easy and quick to fill in the questionnaire. No open-ended questions where asked.

4- A first draft of the survey was produced. A simple tabular structure is adopted to facilitate the completion of the questionnaire. A seven-point rating scale (between 0 and 6) was used for the questions, which involve rating the listed bidding factors. This allows a finer discrimination between the measured factors (TEO, 1990). However, it is not recommended to use finer rating scales because the human cognitive capabilities are generally limited to dealing with no more than seven concepts simultaneously (Saaty 1977).

5- Several loops were made for:
  - Checking and modifying how questions are worded and ordered;
  - Adding or removing certain questions; and,
  - Improving the questionnaire's layout to make it looks attractive, not complicated and easy to answer.

A complete chick list can be found in De Vans (1991) to ensure a good wording of the questions. The procedure proposed by Parasuraman (1991) and presented in Fig. 4.1 was used to produce the final draft of this questionnaire.

#### 4-5-1-2 Structure of the Questionnaire A

The final draft of the questionnaire is organised into three parts in addition to a concise covering letter stating what the study is all about as shown in appendix A. Part one is devoted to the general information about respondents and the current bidding practice. Questions included in this part are regarding the following aspects:

1- Typical type(s)/size of projects the respondent usually deals with;

2- Minimum capital required to bid for a new project;
3- Current degree of competition/number of competitors;
4- Current method used in making the bidding decisions;
5- Number of projects tendered for/obtained per year; and
6- Years of experience.

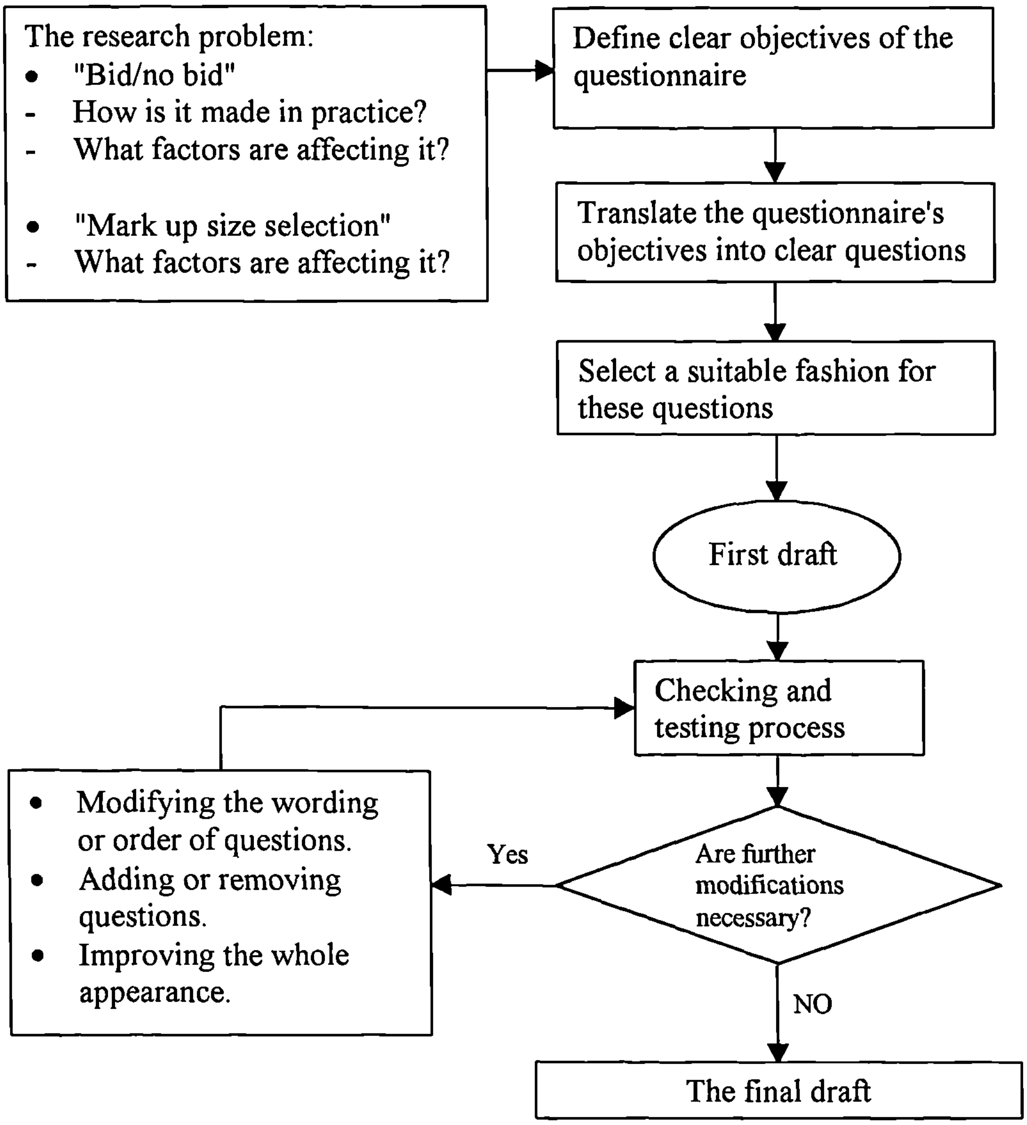



Fig. 4.2: The development of questionnaire A

Part two aims at identifying the importance of the bidding factors. Respondents were requested to assign suitable rating to these factors on a scale from 0, i.e. extremely low, to 6, i.e. extremely high, based upon their respective judgement and experience. These ratings highlight the effect and imply the relative importance of these factors in making the bidding decisions. Thirty four factors are listed in a tabular structure. Each factor along with a scale from 0 to 6 for the importance in making the "bid/no bid" decision and a similar scale for the mark up decision. These factors were compiled from the relevant literature, the author's personal experience on the Syrian construction industry and discussions with experienced general contractors. As mentioned in section 4.9, another two factors ("financial capability of the client", and "proportions that could be constructed mechanically") were added before distributing the questionnaire as suggested by the majority of interviewees. Respondents were requested to add any other missing factors they consider important when making the bidding decisions. Part three is composed of two tables. The first one contains those factors that usually encourage the "bid" decision when assigned high scores (encouraging factors). The other factors (discouraging factors) are listed in the second table (Wanous et al, 1999, 2000a). Respondents are prompted to select a score for each encouraging factor below which the respective factor will have negative effect on the "bid" decision and a score for each discouraging factor above which the respective factor will have a negative effect on the "bid" decision. Also, space is available for missing factors in both tables.

#### 4-5-1-3 Sample Selection and Response Rate

The sample was selected from the 1996 classified private contractors list provided by the Syrian Contractors Association. The following formula was implemented to determine the required sample size (Parasuraman, 1990):

$$n_{\max} = \frac{z_q^{\,2} \times s^2}{H^2} \qquad (4.1)$$

Where:

$n_{\max}$ is the sample size;

s is the estimated standard deviation in the population elements;

$z_q$ is the normal standard-deviate value corresponding to a q% confidence level in the interval estimate; and

H is the desired level of precision.

For normal distribution, the standard deviation (s) can be estimated as follows:

s = (maximum value-minimum value)/6 (4.2)

For this study, the contractors' years of experience was considered as the population's parameter. The list, i.e. sampling frame, provided by the Syrian Contractors Association contained 2231 contractors (the total population) with (1 to 35) years of experience. The normal distribution was assumed. Thus the standard deviation could be estimated using formula (2):

s = (35-1)/ 6 = 5.667

Also, for a normal distribution, we can estimate the mean value (years of experience) as: M= (35-1)/2 =16 years

The mean value "years of experience" of the required sample was considered to be acceptable in the range M ± 2 years, i.e. H = 2.

To achieved that in 99% confidence level ($z_q$ = 2.575), the formula (1) can be used to calculate the required sample size as follows:

$n_{max} = (2.575)^2 * (5.667)^2 / 2^2 = 53.25$

A sample of fifty responses was assumed to be enough to give an indication of the importance level for each of the bidding parameters. Response rate of 25% was expected, thus 200 contractors were randomly selected and approached by the way of questionnaire (A) along with an accompanying letter explaining the purpose of the survey. Stamped self-addressed envelopes were enclosed for the return of questionnaire.

Sixty one Syrian contractors filled in and returned the questionnaire. The response rate was higher than expected (30.5%). Telephone calls and personal visits helped to get this good response rate.

**4-6 Interviews Findings: The Current Bidding Practice in Syria**

The interviewees described the tendering procedures used in the Syrian construction industry and explained how they usually make the bidding decisions in practice. The two most frequently used tendering procedures in the Syrian construction industry are:

1. Addition/Reduction Tender (A/RT): In this case the client's design department produces the project's cost estimate, bill of quantities (all items are included with their standard units, quantities, individual prices and cumulative prices), detailed specifications, drawings and the codes of technical, financial, and legal conditions. Then the project is advertised in the Bulletin of Official Tenders (BOTs) and, sometimes, in the local/national newspapers. Interested contractors can compete on this project by submitting a tender, which is a commitment to construct the project within the client-estimated cost increased or reduced by a certain percentage, which would be compared with other competitors' addition or reduction percentages.
2. Price Offer Tender (POT): Very similar to A/RT but the client is not involved in a detailed cost estimate. The bills of quantities contain only the items' descriptions, standard units, and approximate quantities. Interested contractors fill in the missing individual prices and cumulative prices for each item and then, by summing up the cumulative prices, calculate the final price, which would be compared to other competitors' prices.

The contract is generally awarded to the lowest bidder in both tendering procedures. All interviewees agreed that they relay on their experience to make the bidding decision indicating the absence of any decision-support system, which validates the hypothesis of this study (see section 1.4). They stated that every registered contractor regularly receives a copy of the BOTs, which is an open invitation to bid on a very wide range of projects that the construction industry's clients (usually the public sector agencies) intend to construct. The BOTs usually contain important information about each of the advertised projects including the project location; project type; bids' submission date; the type of tender (usually A/RT or POT); and expected duration (see Wanous et al 1998). Contractors start with skimming through the BOTs with attention paid to the following points:

1. Relations with/ reputation of clients;
2. Financial capability of clients;
3. Project Size;
4. Fulfilling the to-tender conditions imposed by clients;
5. Availability of capital required; and,

6. Availability of time for tendering.

After considering these factors, if "no bid" decision has not been made, contractors will proceed and buy a copy of the related conditions, specifications and drawings, usually, from the client's contract division. Site visits are used to obtain information regarding:

1. Exact project location;
2. Site accessibility;
3. Site clearance of obstructions;
4. Site geological conditions;
5. Availability of local labour;
6. Availability of local resources for the required materials;
7. The public exposure; and,
8. Similar projects constructed in the same area and what can be learnt from them.

Contractors study, in some details, the related drawing, specifications, and the other financial and legal conditions. In this stage the following points are emphasised:

1. Risks expected due to the project's nature;
2. Method of construction (manually or mechanically); and,
3. Rigidity of the project specifications and the legal conditions.

Contractors also consider other factors (e.g. experience on similar projects, availability of equipment, availability of other projects). If a contractor decided to bid, a quick cost estimation is prepared. Usually the contractor calculates the detailed direct costs (materials, labour, equipment, and subcontractors) for each item included in the project's bill of quantities. To complete this task, a general practical plan is established to give an image of how and when each item of the project can be constructed. To establish this plan, the contractor studies the project's drawings and relies on his experience to develop an imaginary image of how the work could be done and what problems (risks) could occur during construction. As a result, some of the project risks are accounted for within the project's direct cost. On the other hand, the interviews revealed that most Syrian contractors estimate the project's indirect costs (costs cannot be attributed to a certain item such as overheads, taxes, and insurance) as a percentage of the project's direct cost. Having the direct and indirect costs estimated, a suitable competitive mark up percentage is determined. That depends upon the project characteristics, the available resources, the construction market, and, less importantly, the client's characteristics that have more influence on the "bid/no bid" decision. A flowchart is presented in Fig. 4.3 to summarise the bidding process as explained by the interviewees.

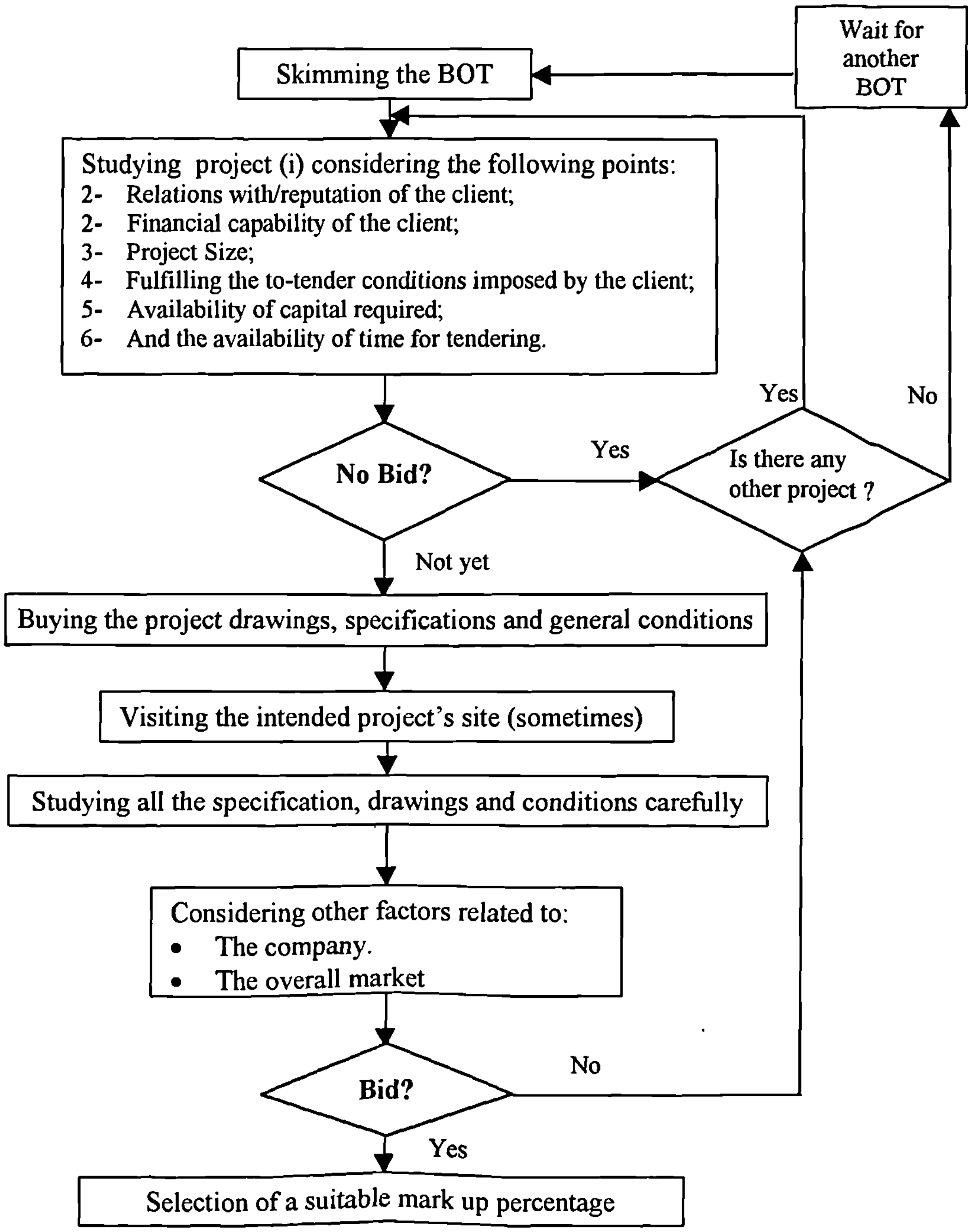



Fig. 4.3: The practice of making the bidding decisions

The main aim of the interviews is to know the current bidding practice and to collect some supportive knowledge but not to identify the importance of the bidding factors. Therefore, it was not felt necessary to conduct more interviews or to consider the exact factors that were mentioned by each interviewee. Rather, an outline of the interviewees' statements was considered to be adequate for the purpose of the present study.

## 4-7 Interviews Findings: Critical Effect of Some Individual "Bid/no Bid" Factors

Usually contractors combine the effects of many factors and then decide whether to bid or not. Primarily, they referred to their long-term experience in the construction industry. But, contractors were not able to explain how. This confirms the views of Hutchinson *et al* (1987) and Bramer (1987) that much of the expert knowledge is used in a subconscious manner. During the interviews, no single factor was considered to be enough for making the "bid" decision but sometimes a single factor could be enough to cause a "no bid" decision. Each one of the factors shown in Tables 4.1 and 4.2 was considered by some interviewees to be enough to cause a "no bid" decision in itself. The third column of each table shows how many interviewees have considered each factor as a critical one. Interviewees suggested a kill-score ($NB_i$) on a predefined scale from 0 (extremely low) to 6 (extremely high) for each factor in Table 4.1. Below $NB_i$ they would not bid. Also, interviewees suggested a kill-score ($NB_j$) for each factor in Table 4.2. Above ($NB_j$) they would not bid. The most frequently suggested values of $NB_i$ or $NB_j$ are shown in the last column of each table.

Table 4.1: Kill-scores of positive "bid/no bid" factors

| *i* | **Factors** | **No. of interviewees** | **Kill-score $NB_i$** |
|---|---|---|---|
| 1 | Fulfilling the to-tender conditions | 6 | 5 |
| 2 | Availability of capital required | 4 | 2 |
| 3 | Financial capability of the client | 5 | 2 |
| 4 | Relations with and reputation of the client | 4 | 2 |
| 5 | Availability of materials required | 4 | 2 |
| 6 | Experience in similar projects | 4 | 2 |

*$NB_i$ is a score below which $F_i$ will cause a "no bid" decision*

Table 4.2: Kill-scores of negative "bid/no bid" factors

| *j* | **Factors** | **No. of interviewees** | **Kill-score $NB_j$** |
|---|---|---|---|
| 1 | Project size | 5 | 5 |
| 2 | Public objection | 4 | 4 |

*$NB_j$ is a score above which $F_j$ will cause a "no bid" decision*

## 4-8 Interviews Findings: The Components of the Mark up Size

The components of the mark up include profit, risk contingencies, and general overheads. However, different bidders apply different mark up policies (Drew and Skitmore, 1997). The interviewees stated that most Syrian contractors add contingencies based on the risk of each item being estimated to the direct cost estimate. They include the general overheads in the indirect cost and then apply a standard mark up to the total estimate to cover profit and some unforeseen risks not compensated for in the cost estimate. This is very much in line with the findings of De Neufville and King (1991). The Syrian contractors consider the mark up as net profit and allowance for some risks that are difficult to be estimated. Nevertheless, most of the interviewees stated that it is impossible for a contractor to account for all the expected risks and stay in business in the current highly competitive construction market.

## 4.9 Interviews Findings: Modifications to the Formal Questionnaire

At the end of the interviews, each contractor was given a copy of the formal questionnaire survey and requested to comment on the questions used and the factors included in this questionnaire. Adding two factors was strongly recommended by four interviewees. These factors are:

a- Financial capability of the client; and

b- Proportions of the work that can be constructed mechanically.

Three interviewees raised their concern about two factors; "degree of hazard" and "availability of skilled staff". They said that these factors are similar to other factors ("risks expected" and "availability of skilled labour" respectively). Two interviewees stated that one of the main sources of risks is the uncertain geological information available about the project site. Therefore, this factor can be removed from the questionnaire list, as it is included in the "risks expected" factor. Initially, it has been decided to keep these factors in the list because the majority of interviewees did not suggest removing them. The interviews were used only to identify the current bidding practice and to collect some supportive knowledge. The following sections explain the design and the findings of the two formal questionnaires used to collect the main body of the required data.

## 4.10 Findings of Questionnaire A: Background Information

Part one of the questionnaire aimed at collecting background information on contractors involved in the civil engineering construction industry and some general information on the current tendering practice in Syria.

### 1- Type of contractors

The majority of contractors (83.6%) performed various building projects including housing, industrial, educational, and office buildings. The second most popular project type among participants is pipeline (55.7%) as shown in Fig.4.4, 45.5% of them performed road projects. Dam-type of projects is one of the typical projects of 41% of the contractors surveyed. Very few contractors undertake special projects such as power stations, airports, seaports, and oil projects.

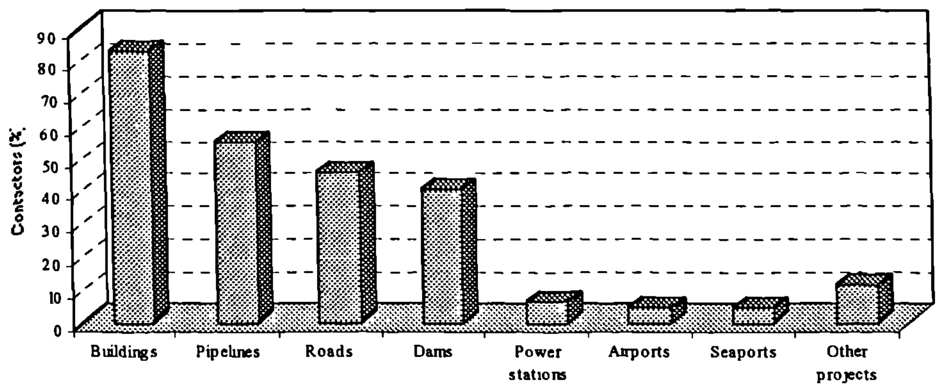



Fig. 4.4: Typical projects undertaken by participants

### 2- Typical size of projects undertaken by the surveyed contractors

The largest group of contractors (26.23%) undertake projects in the range between 70 and 100 million Syrian pounds (£1≈ 60 Syrian pound). The typical project size of the second largest category (19.67%) is more than 100 million Syrian pound. 13.11% of contractors perform projects in the range between 50 and 70 million. 13.11%

preferred not to disclose the typical size of their projects presumably for confidentiality reasons. The remaining contractors are usually interested in medium and small projects (less than 50 million) as shown in Fig. 4.5.

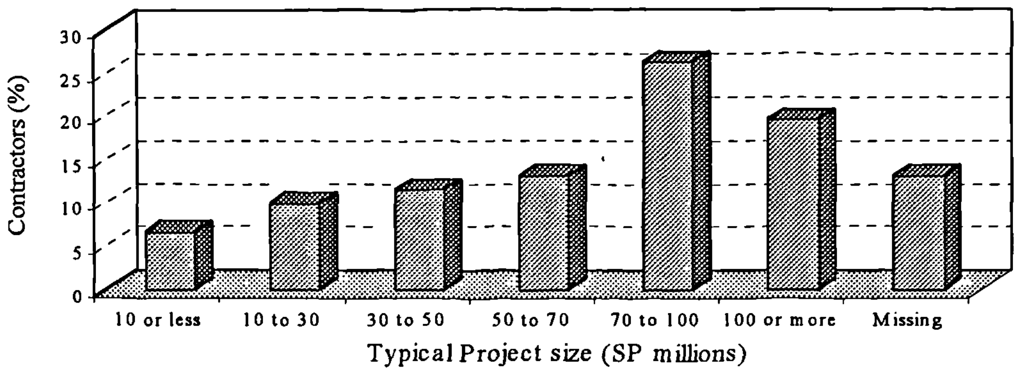



Fig. 4.5: Typical size of projects undertaken by participants

**3- Minimum capital required for bidding on a new project**

Contractors are expected to start construction projects depending solely on their financial resources. Contractors were requested to estimate the minimum capital required when submitting a new bid as a percentage of the project size. The suggested range (see Fig. 4.6) is between 18% and 25% of the project size with an average of 21% and a relatively low dispersion (StD=0.016).

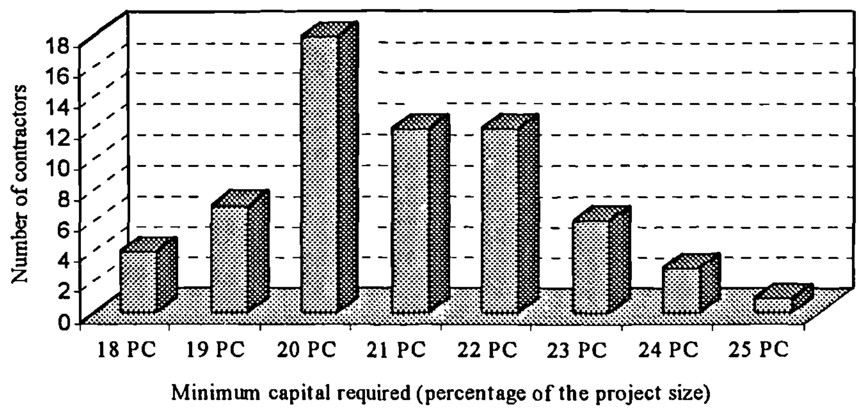



Fig. 4.6: Minimum capital required to bid on a new project

**4- Current degree of competition**

The majority of contractors (54.1%) described the degree of competition in the current Syrian construction industry as "very high". The second largest group

(34.43%) described it as "high". The remaining 11.7% assessed the degree of competition as being medium. The judgement of this group may be based on special and large projects such as seaports and airports as very few contractors are capable of undertaking such projects (see Fig. 4.4). Also, a negative correlation has been identified between the typical project size of contractors and their assessment of the current degree of competition (r = -0.393). This suggests that the larger the project the lower the competition is. No contractors assigned low or very low scores to the current degree of competition as shown in Fig. 4.7.

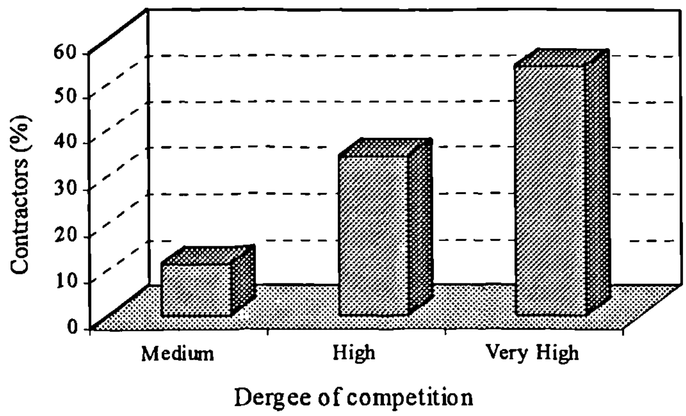



Fig. 4.7: Current degree of competition

**5- Average number of competitors**

As suggested by the majority of participants (56.5%), the average number of competitors is 8 to 10 contractors (see Fig. 4.8). 27.4% stated that average number of competitors is eleven or more. This again reveals the fact that the Syrian construction industry is very competitive.

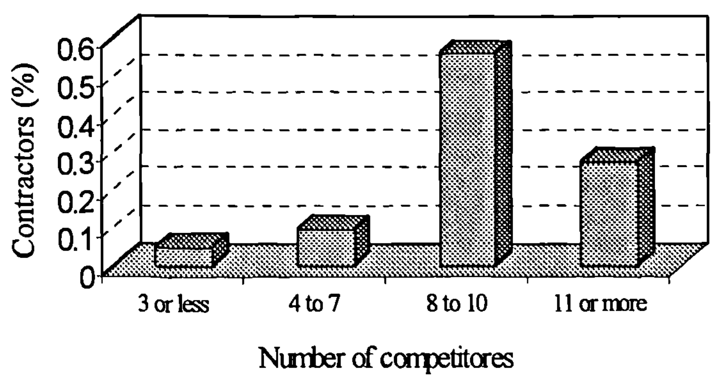



Fig. 4.8: Average number of competitors

**6- Methods of making the bidding decisions**

Almost all contractors rely on their subjective judgement based on past experience to decide whether or not to bid on new projects and to select a suitable mark up percentage. Only two contractors (3.28%) stated that they use some sort of mathematical procedures to make the bidding decisions. However, 11.48% of contractors keep information about their common competitors and they refer to this information when making the bidding decisions. Similar studies have pointed out that there is little use of mathematical and statistical bidding models in various countries as shown in Table 4.3. All these studies have emphasised the need for qualitative models instead.

Table 4.3: The use of mathematical bidding methods in various countries

| Country | Contractors using some sort of mathematical bidding methods (%) | Researcher(s)/ Year |
|---|---|---|
| USA | 11.1 | Ahmed and Minkarah /1988 |
| UK | 17.6 | Shash/ 1993 |
| Australia | 12.0 | Ting and Mills/ 1996 |

**7- Ratio of successful bids**

The average number of bids submitted by one contractor in a year is (9.71). Contrary, the average number of successful bids per year is only (1.23), i.e. only one bid is successful and seven are abortive out of each eight attempts. This high proportion of abortive bids is caused to a certain extend by high competition and large number of bidders competing on one project (see Figures 4.7 and 4.8).

**8- Experience of participants**

78.7% of participants have considerable experience (more than 16 years). The largest group of them (32.79%) has been working in the Syrian construction industry for 16-20 years. Another 27.87% of contractors have between 21 and 25 years of experience as shown in Fig.4.9.

## 4.11 Findings of Questionnaire A: Importance of "Bid/no Bid" Factors

One of the main objectives of this study is to identify the important bid/no bid factors considered by Syrian contractors. Some contractors have added additional factors to

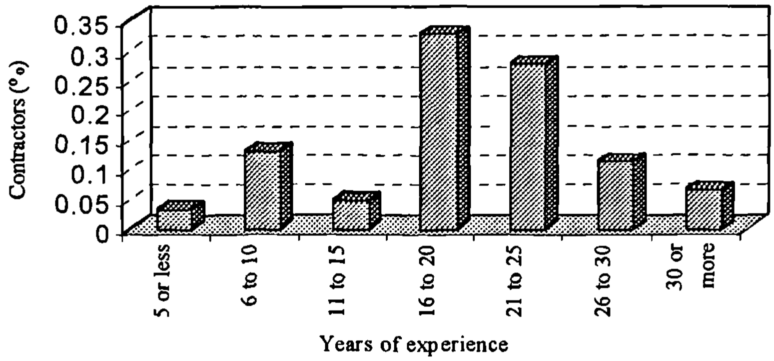



Fig. 4.9: Experience of the surveyed contractors

the questionnaire. The most frequently factors that have been added to the questionnaire list by the surveyed contractors are:

1. Expected date of commencing (by 11 contractors) ; and
2. Specific features that provide competitive advantage (by 9 contractors).

Accordingly, the total number of bidding factors considered in Syria would be thirty eight. Other factors were suggested by less than five contractors. These include:

- Possibility of future work with the same client;
- Potential changes in the original design for which the contractor can claim more profitable prices; and
- Reliability of subcontractors.

Using the scores given by contractors, an importance index ($Ib_j$) was produced for each factor ($F_j$). Ahmad and Minkara (1988) considered the percentage of the respondents who scored a factor of 4 or higher (in a range of 1to 6) as an importance index for this factor. Shash (1993) implemented the following formula:

$$\text{Importance index} = \Sigma\,(a * X) * 100/7 \qquad (4.3)$$

Where:

a: a weight given to the factor in each response ($1 \leq a \leq 7$);

X = n/N;

n: frequency of response;

N: Total number of responses.

Σ (a * X) is the weighted average of (a) [Σ(a * n/N)].

In the present work, the weighted average was produced using the following formula:

$$M_j = \frac{\sum_{i=0}^{i=6}(s_{ij} * n_{ij})}{N_{j}.} \qquad (4.4)$$

Where

$M_j$: the mean importance level of factor $F_j$;

$s_{ij}$: score between 0 and 6 given to factor $j$ by each contractor;

$n_{ij}$: number of contractors who scored factor $j$ by $s_{ij}$;

$N_j$: number of contractors who gave a score to factor $j$. $N_j \leq N = 61$ (total number of respondents). This is to discount the effect of missing values.

The "6" score represents 100% importance. Thus the importance index $Ib_j$ for factor $j$ was computed using the following formula:

$$Ib_j = M_j * \frac{100}{6} \qquad (4.5)$$

Where $Ib_j$ is the importance index of factor $F_j$ in making the "bid/no bid" decision. Table 4.4 represents thirty eight factors in a descending order of importance in making the "Bid/no bid" decision in Syria. Also, the average of the contractors' assessments and the standard deviation of these assessments are provided in Table 4.4. As shown in this table, there is a general consensus in the rating of factors among the sixty one contractors as evidenced by the relatively low standard deviations. In the case of two factors, or more, having the same importance index, the factor whose negative Skewness is greater was ranked first because this indicates that more high scores are greater than the mean. The histograms of contractors' ratings of the top ten important "bid/no bid" factors are shown in Fig. 4.10. Fulfillment of the "to-tender" conditions, i. e. qualifications, imposed by the client was ranked the first among 38 factors. It has been assigned a very high importance (89.88%) but not 100% presumably because a contractor who does not fully meet the required conditions can submit a tender in a partnership with other contractors who do fulfil these conditions. Also, good relations with the client could be another justification. Availability of the required capital was ranked the sixth with a high importance (68.33%), which is less than expected perhaps because contractors can borrow the capital they require until they receive the first payment from the client.

Table 4.4: Bid/no bid factors in a descending order of importance

| *j* | Factors | Standard deviation | Mean ($Mj$) | Importance Index $Ibj$ | |
|---|---|---|---|---|---|
| 1 | Fulfilling the to-tender conditions | 0.525 | 5.39 | 89.88 | * |
| 2 | Financial capability of the client | 1.02 | 4.66 | 77.67 | * |
| 3 | Relations with and reputation of the client | 0.737 | 4.61 | 76.83 | * |
| 4 | Project size | 0.918 | 4.39 | 73.17 | * |
| 5 | Availability of time for tendering | 1.192 | 4.25 | 70.83 | * |
| 6 | Availability of capital required | 0.889 | 4.10 | 68.33 | * |
| 7 | Site clearance of obstructions | 0.988 | 4.08 | 68.00 | * |
| 8 | Public objection | 1.031 | 4.07 | 67.83 | * |
| 9 | Availability of materials required | 1.072 | 3.98 | 66.33 | * |
| 10 | Current workload | 1.048 | 3.95 | 65.83 | * |
| 11 | Experience on similar projects | 0.734 | 3.84 | 64.00 | * |
| 12 | Availability of equipment required | 0.986 | 3.84 | 64.00 | * |
| 13 | Proportions that can be constructed mechanically | 1.110 | 3.84 | 64.00 | * |
| 14 | Availability of skilled labour | 1.058 | 3.48 | 58.00 | * |
| 15 | Availability of qualified staff | 1.237 | 3.34 | 55.67 | |
| 16 | Original project duration | 1.012 | 3.33 | 55.50 | * |
| 17 | Site accessibility | 1.039 | 3.23 | 53.83 | * |
| 18 | Risks expected | 1.081 | 3.13 | 52.17 | * |
| 19 | Degree of hazard | 1.072 | 3.13 | 52.17 | |
| 20 | Rigidity of specifications | 1.252 | 3.00 | 50.00 | * |
| 21 | Expected project cash flow | 1.420 | 2.82 | 47.00 | * |
| 22 | Degree of builability | 1.466 | 2.82 | 47.00 | * |
| 23 | Availability of other projects | 1.100 | 2.77 | 47.17 | * |
| 24 | Confidence in the cost estimate | 1.020 | 2.72 | 45.33 | * |
| 25 | The project geological study | 1.309 | 2.41 | 40.17 | |
| 26 | Project location | 1.076 | 1.90 | 31.67 | |
| 27 | Original price estimated by the client | 0.989 | 1.71 | 28.50 | |
| 28 | Past profit in similar projects | 1.070 | 1.59 | 26.50 | |
| 29 | Expected date of commencing | 1.219 | 1.48 | 24.67 | |
| 30 | Availability of equipment owned by the contractor | 1.287 | 1.33 | 22.17 | |
| 31 | Expected Degree of competition | 0.854 | 1.07 | 17.83 | |
| 32 | Local climate | 0.644 | 1.05 | 17.50 | |
| 33 | Specific features that provide competitive advantage | 0.806 | 0.98 | 16.33 | |
| 34 | Fluctuation in labour/ materials price | 0.625 | 0.90 | 15.00 | |
| 35 | Competence of the expected competitors | 0.789 | 0.75 | 12.50 | |
| 36 | Relations with other contractors and suppliers | 0.820 | 0.62 | 10.33 | |
| 37 | Proportions to be subcontracted | 0.655 | 0.33 | 5.50 | |
| 38 | Local customs | 0.471 | 0.25 | 4.17 | |

*- *See Section 4.14*

On the other hand, a moderate importance was assigned to the expected risks. Surprisingly the project location was assessed as a very low important factor in the bidding decision. Competition is not very important when making the "bid/no bid" decision. Degree of competition and competence of the expected competitors were ranked thirty second and thirty sixth respectively. Fluctuation in labour/materials' prices has little effect on "bid/no bid" decision because labour/materials' prices are currently very stable in Syria.

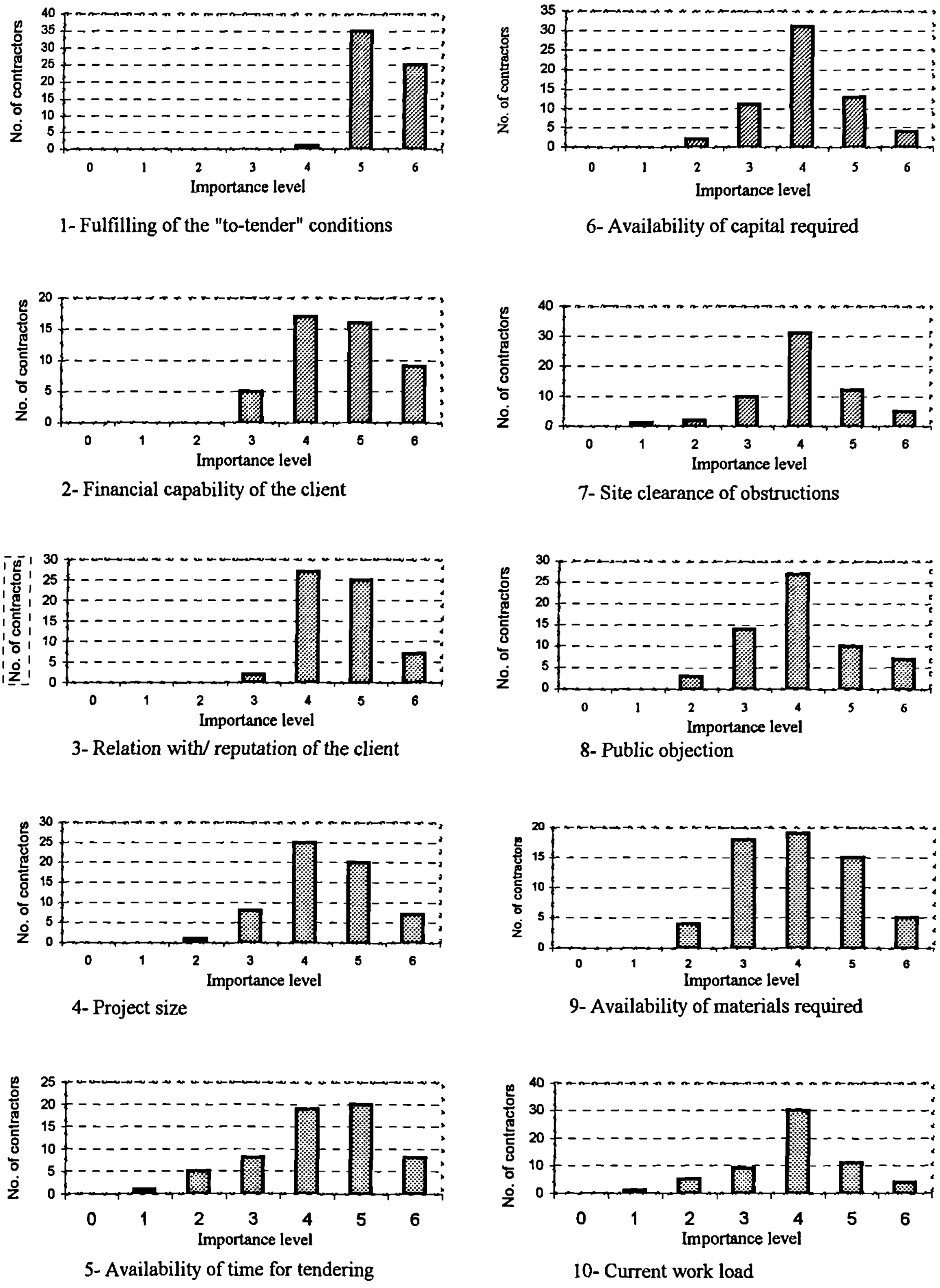



Fig. 4.10: Profiles of the ten most important "bid/no bid" factors

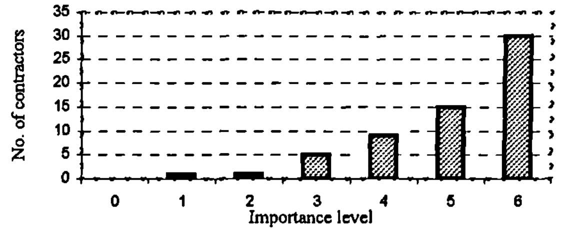
## 4.12 Findings of Questionnaire A: Importance of Mark up Factors

The index of importance of a certain factor in making the mark up decision was produced using Equations 4.4 and 4.5. This index is denoted as ($Im_j$) to distinguish it from the index of importance in making the "bid/ no bid" decision ($Ib_j$). Table 4.5 represents the same 38 bidding factors in a descending order of importance in making the mark up selection decision based on the subjective ratings provided by Syrian contractors.

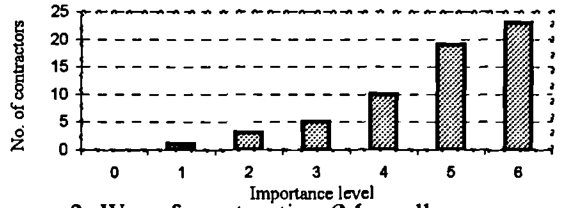
Table 4.5: Mark up factors in descending order of importance

| $i$ | Factors | Standard Deviation | Mean ($Mj$) | Importance Index $Imj$ | |
|---|---|---|---|---|---|
| 1 | Risks expected | 0.911 | 5.32 | 88.67 | * |
| 2 | Degree of hazard | 1.181 | 5.07 | 84.43 | |
| 3 | Competence of the expected competitors | 1.143 | 5.02 | 83.67 | * |
| 4 | Expected Degree of competition | 1.297 | 4.95 | 82.50 | * |
| 5 | Rigidity of specifications | 1.163 | 4.73 | 78.83 | * |
| 6 | Availability of materials required | 1.076 | 4.70 | 78.33 | * |
| 7 | Degree of builability | 1.008 | 4.63 | 77.17 | * |
| 8 | Confidence in the cost estimate | 1.408 | 4.51 | 75.17 | * |
| 9 | Availability of equipment required | 1.284 | 4.12 | 68.67 | * |
| 10 | Project size | 1.087 | 3.93 | 65.50 | * |
| 11 | Availability of equipment owned by the contractor | 1.254 | 3.92 | 65.33 | * |
| 12 | Public objection | 1.245 | 3.87 | 64.50 | * |
| 13 | Proportions that can be constructed mechanically | 0.710 | 3.75 | 62.50 | * |
| 14 | Site accessibility | 1.311 | 3.69 | 61.50 | * |
| 15 | Project location | 1.106 | 3.62 | 60.33 | * |
| 16 | Site clearance of obstructions | 1.148 | 3.53 | 58.83 | * |
| 17 | Original project duration | 1.156 | 3.45 | 57.50 | * |
| 18 | The project geological study | 1.309 | 3.41 | 56.83 | |
| 19 | Availability of skilled labour | 1.081 | 3.36 | 56.00 | * |
| 20 | Current work load | 1.439 | 3.28 | 54.67 | * |
| 21 | Availability of qualified staff | 1.059 | 3.25 | 54.17 | |
| 22 | Experience on similar projects | 1.193 | 3.10 | 51.67 | * |
| 23 | Availability of capital required | 1.374 | 2.53 | 42.17 | * |
| 24 | Local climate | 1.391 | 2.36 | 39.33 | |
| 25 | Fluctuation in labour/ materials price | 0.82 | 2.16 | 36.00 | |
| 26 | Past profit in similar projects | 1.653 | 2.00 | 33.33 | |
| 27 | Availability of other projects | 1.207 | 1.97 | 32.83 | |
| 28 | Specific features providing competitive advantage | 0.790 | 1.95 | 32.50 | |
| 29 | Proportions to be subcontracted | 1.383 | 1.95 | 32.50 | |
| 30 | Availability of time for tendering | 1.672 | 1.95 | 32.50 | |
| 31 | Relations with and reputation of the client | 1.674 | 1.89 | 31.50 | |
| 32 | Relations with other contractors and suppliers | 1.645 | 1.84 | 30.67 | |
| 33 | Expected project cash flow | 1.617 | 1.78 | 29.67 | |
| 34 | Original price estimated by the client | 1.731 | 1.57 | 26.17 | |
| 35 | Fulfilling the to-tender conditions | 1.501 | 1.52 | 25.33 | |
| 36 | Financial capability of the client | 1.030 | 1.22 | 20.33 | |
| 37 | Local custom | 1.560 | 1.00 | 16.67 | |
| 38 | Expected date of commencing | 1.388 | 0.93 | 15.50 | |

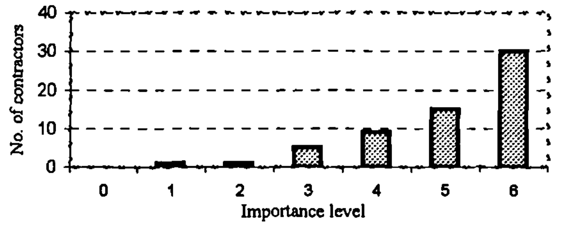
**- See Section 4.15*



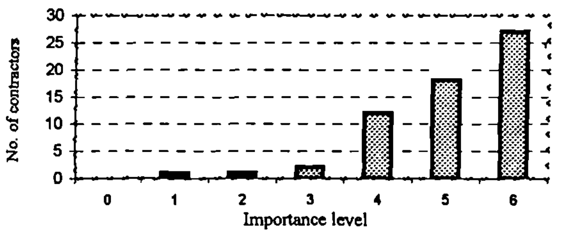
1- Risks expected



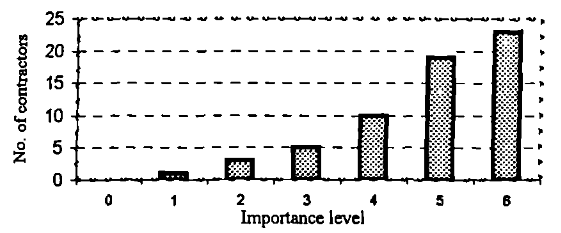
2- Way of construction (Manually or mechanically)



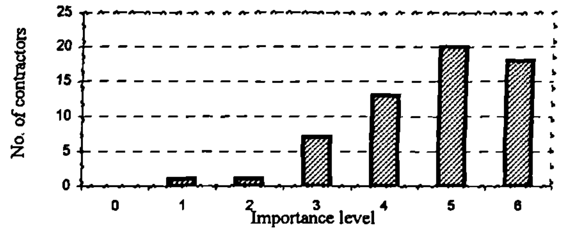
3- Degree of hazard



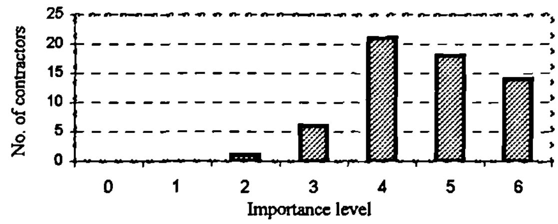
4- Site clearance of obstructions



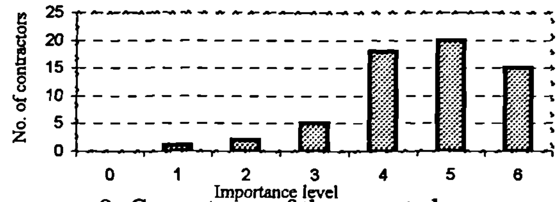
5- Availability of equipment owned by the contractor



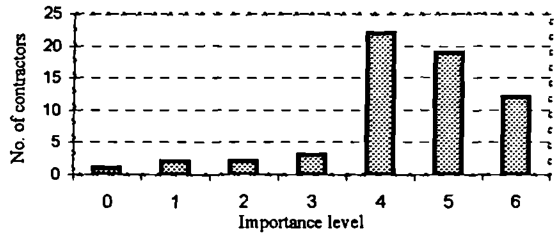
6- Rigidity of specifications



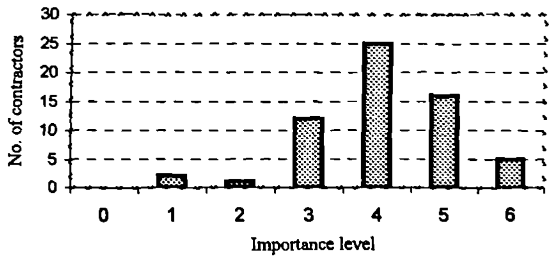
7- Degree of buildability



8- Competence of the expected competetors



9- Expected number of competetors



10- Availability of materials required.

Fig. 4.11: Profiles of the ten most important mark up factors

The average and standard deviation of the contractors' assessments and the importance index are provided for each factor. The second most influential mark up factor is the volume of project proportions that can be constructed mechanically. This confirms the legitimate judgement of the interviewed contractors when they suggested adding this factor to the questionnaire survey. Fig. 4.11 shows the histogram of the top ten important mark up factors plotted according to the contractors' subjective ratings of their importance. The significant negative skewed distributions (especially of the first five factors) indicate the extreme importance of these factors in the mark up selection process. Unsurprisingly, the expected risks have the greatest influence on the mark up size. One of the main component of the mark up percentage is the risk contingencies . It is worth noting that the same factors affect the both "bid/no bid" and mark up decisions but to different degrees. For example risks expected, which is the first amongst thirty eight factors that affect the mark up decision (Im = 88.67%) is the eighteenth "bid/ no bid" criterion (Ib = 52.17%). Contrary, fulfilment of the "to-tender" conditions is the most important factor in making the "bid/no bid" decision (Ib = 89.88%) but it has a little influence on the mark up size (it is the thirty fifth factor and Im = 25.33%). Factors such as the availability of skilled labour have moderate effect on both decisions.

## 4.13 Findings of Questionnaire A: Neutral Scores of the "Bid/no Bid" Factors

Statistical analysis was performed on the contractors' responses in part three of questionnaire (A) (see section 4.5.1.2 and appendix A) to select suitable values for the neutral scores of the considered "bid/no bid" factors. The average and the standard deviation of the contractors' recommendations were produced. The average was considered as the initial value of the neutral score. Other values can be produced as a function of the average and the standard deviation if required. Table 4.6 shows the neutral scores of the positive "bid/no bid" factors ($B_i$). The neutral scores of the negative factors ($B_j$) are shown in Table 4.7.

Table 4.6: Neutral scores of the positive "bid/no bid" factors

| $i$ | Positive "bid/no bid" Factors | Neutral Score ($B_i$) | |
|---|---|---|---|
| | | StD | Mean |
| 1. | Fulfilling the to-tender conditions imposed by the client | 0.37 | 5.84 |
| 2. | Financial capability of the client | 0.88 | 3.48 |
| 3. | Good relations with and reputation of the client | 0.73 | 3.84 |
| 4. | Availability of time for tendering | 1.09 | 2.54 |
| 5. | Availability of capital required | 0.73 | 3.41 |
| 6. | Site clearance of obstructions | 0.90 | 3.64 |
| 7. | Availability of materials required | 0.90 | 3.56 |
| 8. | Experience in similar projects | 0.74 | 3.61 |
| 9. | Availability of equipment required | 0.84 | 3.40 |
| 10. | Proportions that can be constructed mechanically | 0.72 | 3.05 |
| 11. | Availability of skilled labour | 0.83 | 3.25 |
| 12. | Availability of skilled staff | 0.79 | 3.19 |
| 13. | Sufficiency of the original project duration | 1.03 | 3.00 |
| 14. | Site accessibility | 0.79 | 3.02 |
| 15. | Favourability of the expected cash flow | 1.08 | 2.80 |
| 16. | Degree of buildability | 1.11 | 2.28 |
| 17. | Confidence in the cost estimate | 0.73 | 3.85 |
| 18. | Estimated accuracy of the project geological study | 1.11 | 2.47 |
| 19. | Sufficiency of the original cost estimated by the client | 1.32 | 2.15 |
| 20. | Past profit in similar projects | 1.22 | 2.11 |
| 21. | Suitability of the expected commencing date | 0.93 | 2.85 |
| 22. | Availability of owned equipment | 0.80 | 1.02 |
| 23. | Specific features that provide competitive advantage | 0.71 | 0.89 |
| 24. | Good relations with other contractors/ suppliers | 0.42 | 0.75 |
| 25. | Proportions to be subcontracted | 0.45 | 0.72 |
| 26. | Favourability of the local customs | 0.13 | 0.52 |

*$B_i$ is a score below which factor ($F_i$) will have a negative effect on the "bid" recommendation.*

Table 4.7: Neutral scores of the negative "bid/no bid" factors

| $j$ | Negative "bid/no bid" Factors | Neutral Score ($B_j$) | |
|---|---|---|---|
| | | StD | Mean |
| 1. | Project size | 0.65 | 3.69 |
| 2. | Public objection | 0.75 | 2.15 |
| 3. | Current work load | 0.75 | 2.90 |
| 4. | Risks expected | 0.73 | 3.12 |
| 5. | Degree of hazard | 0.71 | 3.08 |
| 6. | Rigidity of specifications | 0.75 | 3.66 |
| 7. | Availability of other projects | 0.76 | 5.21 |
| 8. | Remoteness of the project location | 1.06 | 4.46 |
| 9. | Expected degree of competition | 0.92 | 4.77 |
| 10. | Adversity of the local climate | 1.11 | 4.23 |
| 11. | Fluctuation in labour/ materials prices | 1.24 | 4.12 |
| 12. | Competence of expected competitors | 0.97 | 4.92 |

*$B_j$ is a score below which factor ($F_j$) will have a negative effect on the "bid" recommendation.*

## 4.14 Selection of the Most Important "bid/no bid" Factors

It is generally accepted that only important factors need to be considered. Therefore, on a subjective basis, a cut-off point (Ib = 40%) was selected between important factors and marginal ones.

Thus, the last thirteen factors listed in Table 4.4 were omitted. Furthermore, the "availability of skilled staff" factor was discarded due to a high correlation with the "availability of skilled labour" (r = 0.76), which suggests that these two factors were considered as similar by respondents. For the same reason, another two factors ("degree of hazard" and " project geological study") were discarded. They are similar to or included in the "risks expected" factor. This has been predicted by some interviewees (see section 4.4). The importance indices (Ib) of all bidding factors (shown in Table 4.4) are illustrated in Fig. 4.13, which identifies the omitted factors. The remaining twenty two factors were selected as the most important "bid/ no bid" factors in Syria. Asterisks in the last column of Table 4.4 indicate these factors.

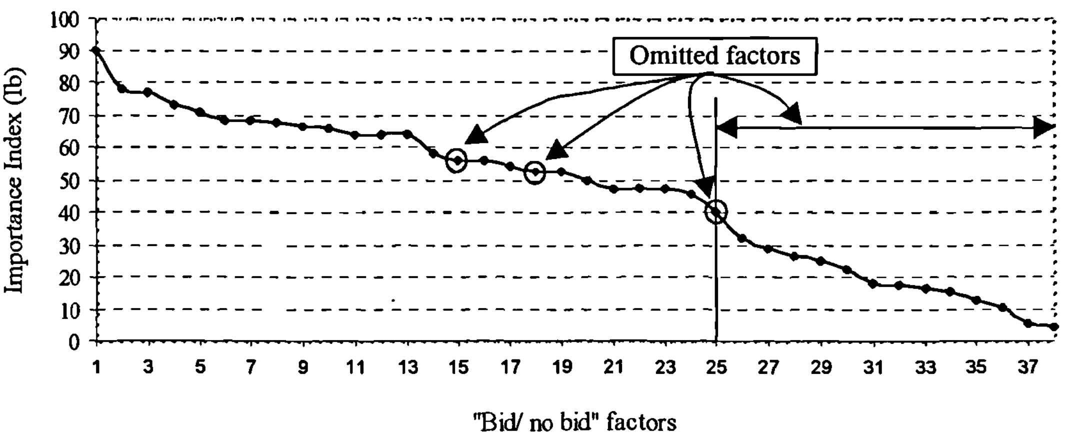



Fig. 4.12: Selection of the most important "bid/no bid" factors

### 4.15 Selection of the Most Important Mark up Factors

Similarly, twenty mark up factors were selected from the whole set presented in Table 4.5. These factors are indicated by asterisks in the last column of Table 4.5. Factors having importance indices less than 40% were omitted in addition to "degree of hazard", "availability of skilled staff", and " the project geological study" factors due their similarity with other factors (see section 4.14).

The importance indices of the 38 mark up factors presented in Table 4.5 are illustrated in Fig. 4.13. The omitted factors are also indicated.

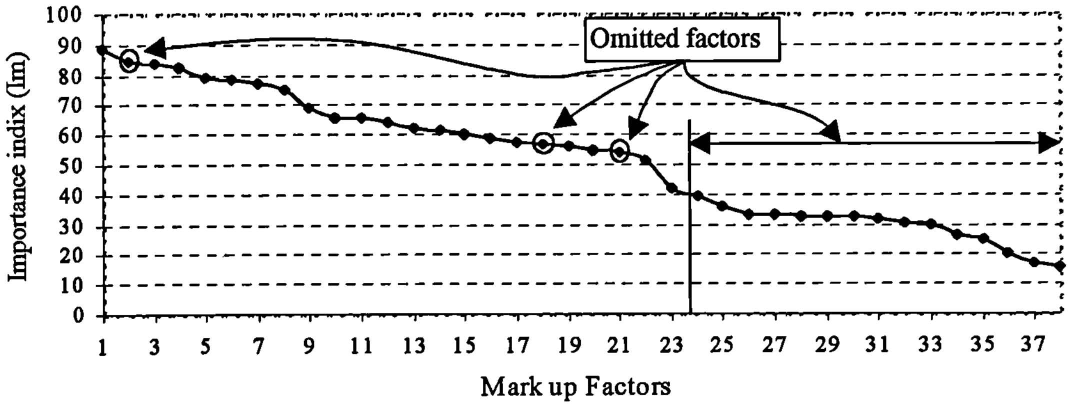



Fig. 4.13: Selection of the most important mark up factors

The identification of the most important factors that affect the bidding decisions is the first most important step of developing any decision-support system to help in making these decisions. However, data of real life bidding situations is required. Therefore, another questionnaire was used to collect this data as explained in the following section.

## 4.16 Questionnaire B

In the last two sections, twenty two factors were nominated as the most important when making the "bid/no bid" decision and twenty factors were nominated as the most important in making the mark up decision. These two sets compile to one set containing twenty six bidding factors. Only these factors were considered to design a simple form (questionnaire B) to be filled in by contractors for each new bidding situation or for recent ones that they can remember or have records of. As shown in Appendix B, this form is composed of the following sections:

1. General information about the project name, size, duration, and type;
2. A tabulated list containing the considered twenty six bidding factors with a scale between 0 (extremely low) and 6 (extremely high). This scale is represented by seven circles along each factor so the contractor can simply tick one of them to provide his subjective assessment of a certain bidding situation in term of the respective factor;

3. The contractor's decision regarding "bid" or " no bid";
4. The adopted tendering procedure, i.e. price offer or addition/reduction ratio. (see section 4.6);
5. The estimated cost (direct and indirect) and the final price; and,
6. The bid outcome (win or loss the contract).

Three hundred copies of questionnaire B were sent to contractors. Basically, they were requested to refer to current/most recent projects, rate the level of each attribute listed in the form, and provide the actual bidding decisions made for each project. One hundred and eighty two forms were filled in and returned. The knowledge depicted in these cases represents the experiences that each of the respondents has gone through directly expressed in a situation-outcome format. This describes the contractors' implicit knowledge and intuitive judgement in assessing the environment of the projects and subsequently making the bidding decisions. Also, the provided cases implicitly reveal to some extend the cause-effect relationships between each factor and the bidding decisions. The main findings of questionnaire B are summarised in the following subsections.

### 4.16.1 Results of Questionnaire B: General Information

The collected bidding situations included a variety of projects; (48.65%) building projects, (18.92%) roads, (29.73%) pipelines, and (2.7%) dams. The average size of these projects is 375.35 million Syrian pounds and the average duration is 19 month. The development of models for specific types or sizes of projects is not possible due to data and time constraints. However, the effect of type and size of a project on the bidding decisions is implicitly accounted for though the subjective assessments of some bidding factors such as "risks expected", "availability of the required capital", "confidence in the cost estimate", and "experience on similar projects". An attempt was made to quantify the effect of the considered 26 factors on the bidding decisions through a simple correlation analysis as explained in the next two sections.

### 4.16.2 Results of Questionnaire B: Influence of the "bid/no bid" Factors

Section 4.11 has identified the most important "bid/no bid" factors according to their importance indices (Ib). The current section is concerned with rating them according to their cause-effect relationships with the actual "bid/no bid" decision made in the real life bidding situations collected. First, the data was checked for completeness. Assessments of some factors were missing. The missing assessment of a certain factor was replaced with the neutral score of this factor based on the findings of questionnaire A. Then, using the SPSS package, correlation analysis was made on one hundred and sixty two cases. Twenty cases were randomly selected and reserved for testing the developed "bid/no bid" models. Table 4.8 shows the previously selected 22 "bid/no bid" factors (see section 4.5.1.8) in a descending order in term of the significance of their relationships (represented by the correlation coefficient r) with the "bid/no bid" decision. The absolute values of (r) are also plotted in Fig.4.14.

Table 4.8: The influence of the most important "bid/no bid" factors

| No. | Factor Name | r | \|r\| | |
|---|---|---|---|---|
| 1 | Fulfilling the to-tender conditions | +0.691 | 0.691 | * |
| 2 | Site accessibility | +0.639 | 0.639 | * |
| 3 | Site clearance of obstructions | +0.570 | 0.570 | * |
| 4 | Availability of capital required | +0.518 | 0.518 | * |
| 5 | Availability of materials required | +0.512 | 0.512 | * |
| 6 | Proportions that could be constructed mechanically | +0.492 | 0.492 | * |
| 7 | Confidence in the cost estimate | +0.456 | 0.456 | * |
| 8 | Financial capability of the client | +0.444 | 0.444 | * |
| 9 | Public objection | -0.432 | 0.432 | * |
| 10 | Current workload | -0.419 | 0.419 | * |
| 11 | Relation with/ reputation of the client | +0.415 | 0.415 | * |
| 12 | Favourability of the cash flow | +0.408 | 0.408 | * |
| 13 | Availability of time to tender | +0.376 | 0.376 | |
| 14 | Project size | -0.360 | 0.360 | |
| 15 | Risks expected | -0.341 | 0.341 | |
| 16 | Experience on similar projects | +0.338 | 0.338 | |
| 17 | Availability of skilled labour | +0.305 | 0.305 | |
| 18 | Rigidity of specifications | -0.301 | 0.301 | |
| 19 | Degree of buildability | +0.285 | 0.285 | |
| 20 | Availability of other projects | -0.247 | 0.247 | |
| 21 | Availability of equipment required | +0.163 | 0.163 | |
| 22 | Sufficiency of the project duration | +0.150 | 0.150 | |

*r Pearson correlation coefficient*

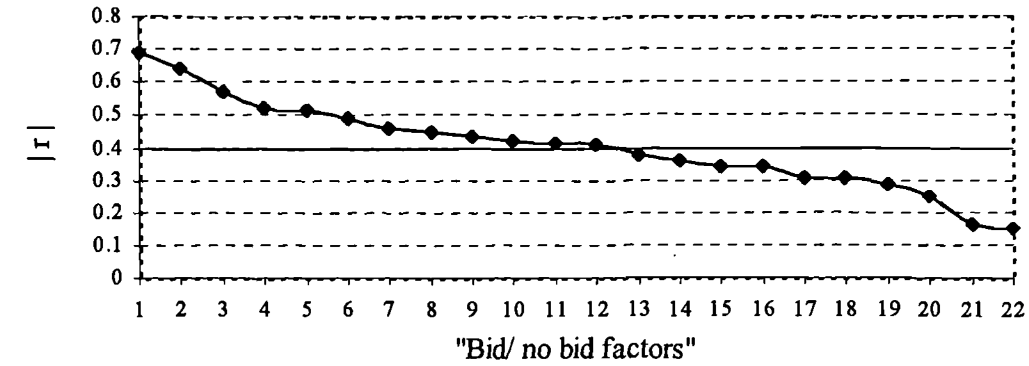



Fig. 4.14: Influence of the "bid/no bid" factors

The following conclusions can be drawn from Table 4.7:

1. All factors that have been classified as negative factors (see section 4.5.1.2) have discouraging effect on the "bid" decision as indicated by their negative correlation with this decision;
2. The order of some factors in term of the significance of their correlation with the "bid/ no bid" decision is considerably different compared to their order based on the importance indices (see Table 4.4). For example, the "site accessibility" is the seventeenth most important factor based on the importance index (Ib = 53.83%) whereas it is the second factor in term of its correlation with the actual decisions in the modelling data (r = 0.639).

Such changes are expected for many reasons, which may include:

- In questionnaire (A), contractors have considered each factor individually when assessing its importance whereas the correlation coefficient (r) of each factor is influenced by the actual decisions, which are the combined outcomes of all factors;
- Some responses on questionnaire (A) might have been influenced by certain degree of idealism, i.e. some contractors might have assigned importance levels to the bidding factors as they think it is right not as it is in real life;

  This is evidence that contractors make the bidding decisions in a subconscious way and they can not easily explain how. In other word, if contractors explained the process of making the bidding decisions, it would not be identical to the real practice.

### 4.16.3 Results of Questionnaire B: Influence of the Mark up Factors

As mentioned earlier, contractors provided data about one hundred and eighty two projects in their responses to questionnaire B. The provided data was checked for completeness. Seventy one cases were not qualified as their mark up values were missing. The remaining one hundred and eleven cases were qualified although some subjective assessments of the bidding situation were not provided. These missing assessments were replaced by (3), i.e. medium. Fifteen projects were randomly selected and reserved for testing and validation of the developed mark up models (validation data). The other ninety six projects will be used in modelling the mark up process (modelling data). The influence of the twenty factors selected in section 4.15 was measured by analysing the relationships between them and the actual mark up values of the modelling data. Table 4.8 shows these factors in a descending order in term of the significance of their correlation coefficients (r). The "risks expected" is the top most influential mark up factor, which confirms to the results of questionnaire A as shown in Table 4.5. However, the influence of other factors such as " proportions that can constructed mechanically" and "confidence in the cost estimate" is greater than what has been suggested by their importance indices. They represent the second and the third factors respectively according to their correlation with the mark up instead of thirteenth and eighth according the their importance indices (see Table 4.5). This suggests that Syrian contractors account for these two factors more than they managed to describe in their responses on questionnaire A, which provides another evidence that bidding process can be described more realistically through real examples rather than asking contractors to articulate the way they make the bidding decisions. The absolute values of (r) are displayed graphically in Fig. 4.15. Nine factors are not significantly correlated with the mark up ($r < 0.5$). These factors can be omitted without considerable negative effect on the accuracy of the modelling process.

The values of the correlation coefficients of the remaining eleven factors (denoted by asterisks in Table 4.9) indicate their significant influence on the mark up size. Therefore, the relationships between these factors and the mark up values in the modelling data were studied in more details as explained in the following section.

Table 4.9: The influence of the most important mark up factors

| No. | Factor Name | r | \|r\| | |
|---|---|---|---|---|
| 1 | Risks expected | 0.711 | 0.711 | * |
| 2 | Availability of equipment owned by the contractor | -0.636 | 0.636 | * |
| 3 | Confidence in the cost estimate | -0.630 | 0.630 | * |
| 4 | Availability of materials required | -0.619 | 0.619 | * |
| 5 | Competence of the expected competitors | -0.614 | 0.614 | * |
| 6 | Degree of buildability | -0.596 | 0.596 | * |
| 7 | Expected degree of competition | -0.577 | 0.577 | * |
| 8 | Proportions that can be constructed mechanically | -0.544 | 0.544 | * |
| 9 | Rigidity of specifications | 0.533 | 0.533 | * |
| 10 | Site clearance of obstructions | -0.528 | 0.528 | * |
| 11 | Site accessibility | -0.514 | 0.514 | * |
| 12 | Availability of capital required | 0.310 | 0.310 | |
| 13 | Public objection | 0.208 | 0.208 | |
| 14 | Remoteness of the project location | 0.199 | 0.199 | |
| 15 | Experience on similar projects | -0.147 | 0.147 | |
| 16 | Availability of skilled labour | -0.088 | 0.088 | |
| 17 | Project size | -0.020 | 0.020 | |
| 18 | Current work load | 0.010 | 0.010 | |
| 19 | Sufficiency of the project duration | 0.007 | 0.007 | |
| 20 | Availability of equipment required | 0.005 | 0.005 | |

*r: Pearson correlation coefficient*

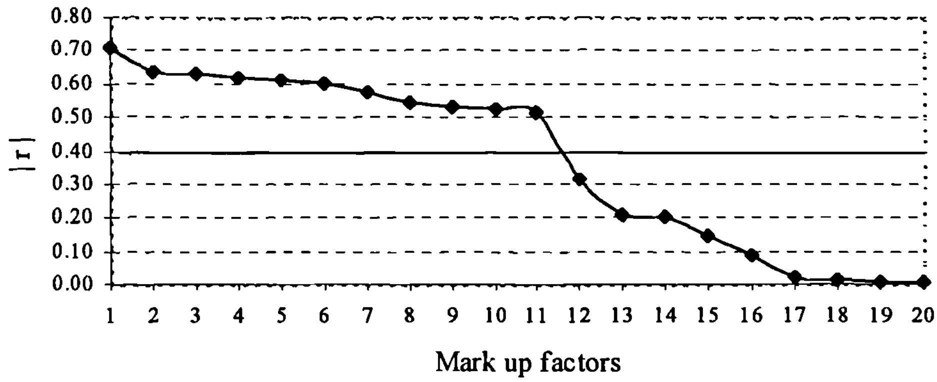



Fig. 4.15: Influence of the mark up factors

### 4.16.4 Results of Questionnaire B: Cause-Effect Analysis

The situation-outcome format of the data collected through questionnaire B has permitted an in-depth analysis of the cause-effect relationships between the bidding criteria and the bidding decisions.

This analysis has been made by developing the best possible regression equation that describes the relationship between the "bid/no bid" decision and each one of the most influential "bid/no bid" factors (see section 4.16.2) using the modelling data. To develop these equations, the actual decisions were transformed into numerical values; 0 for "no bid" and 1 for "bid". Figures 4.16 through 4.27 display the trend lines of the twelve factors whose correlation coefficient are greater than 0.40 (see section 4.16.2) depicted from the "bid/no bid" modelling sample. The results of these self-explanatory graphs are very much in line with the common industry heuristics including the following:

1. High public objection of a certain project will discourage the "bid" decision and visa versa (see Fig. 4.24);
2. Large workload in hand will discourage bidding on new projects (see Fig. 4.25); and,
3. High level of any other factor will encourage the "bid" decision as shown in the remaining figures.

These findings validate the initial classification of the bidding factors into two sets; positive and negative when developing questionnaire A (see section 4.5.1.2). Similar analysis has been made on the most influential mark up factors. The results are illustrated in figures 4.28 through 4.38. The equations shown were generated to best-fit the mark up modelling data to provide a pool of potential parameters to select from when developing the non-linear mark up model (see section 5.4.3). However, as far as the present section is concerned, the general trends depicted in these graphs support the industry common heuristics related to the mark up selection process including the following truisms:

1. Mark up increases when more risks are expected (see Fig. 4.28);
2. Mark up decreases with higher availability of equipment owned by the contractor (see Fig. 4.29);
3. Mark up decreases with higher confidence in the cost estimate (see Fig. 4.30);
4. Mark up decreases with higher availability of the required materials (see Fig. 4.31);
5. Mark up decreases with higher competition (see Fig. 4.34); and
6. Mark up increases with more rigid specifications (see Fig. 4.36).

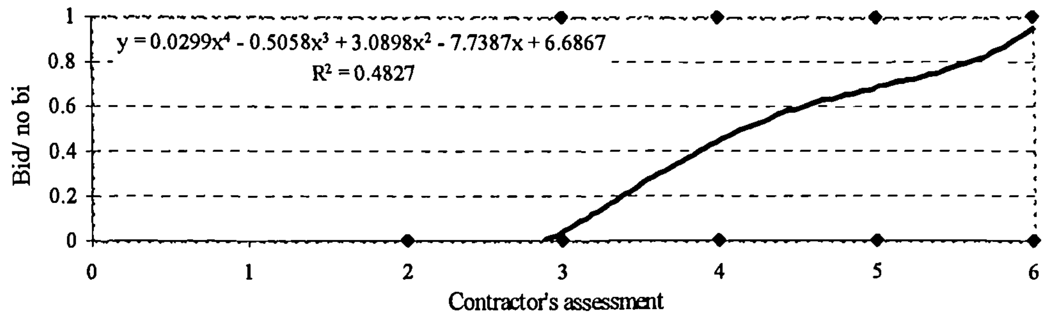



Fig. 4.16: Relationship between bid/no bid decision and fulfilment of the to-tender conditions

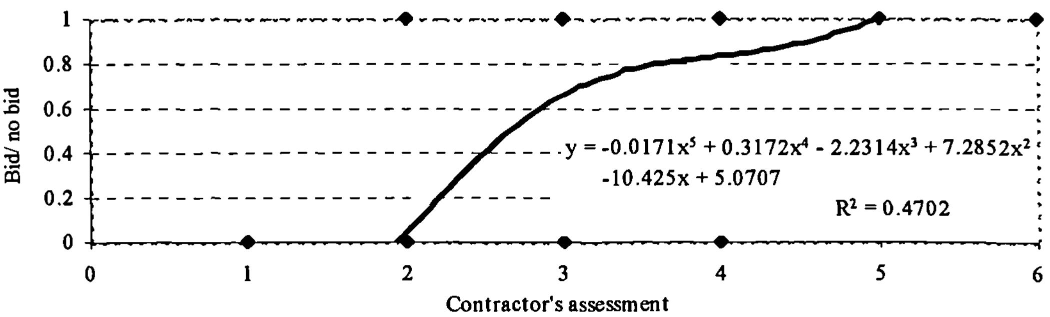



Fig. 4.17: Relationship between bid/no bid decision and site accessibility

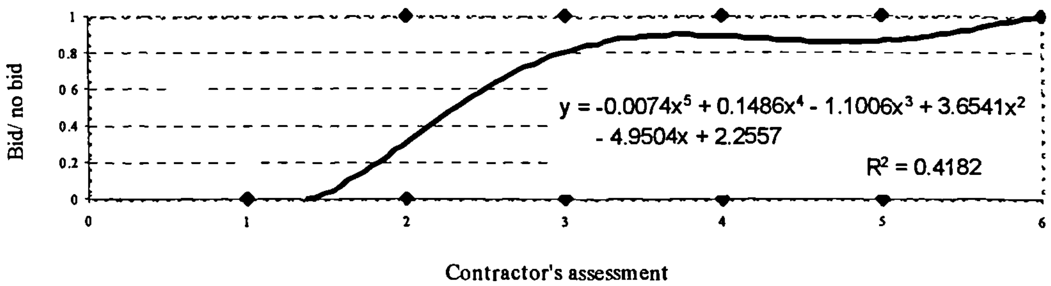



Fig. 4.18: Relationship between bid/no bid decision and site clearance of obstructions

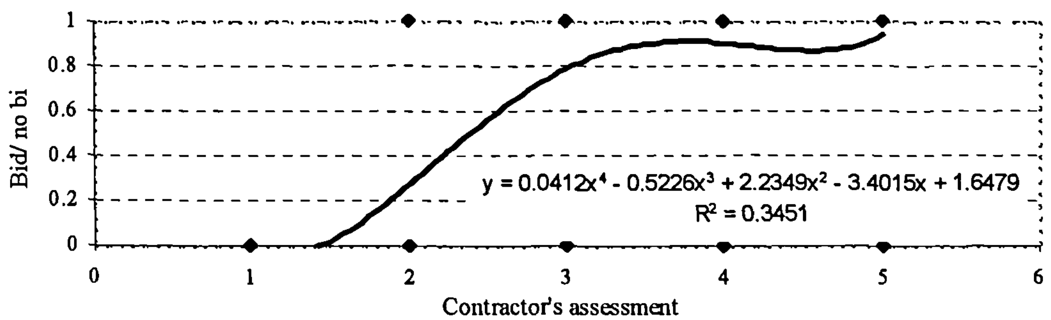



Fig. 4.19: Relationship between bid/no bid decision and availability of capital

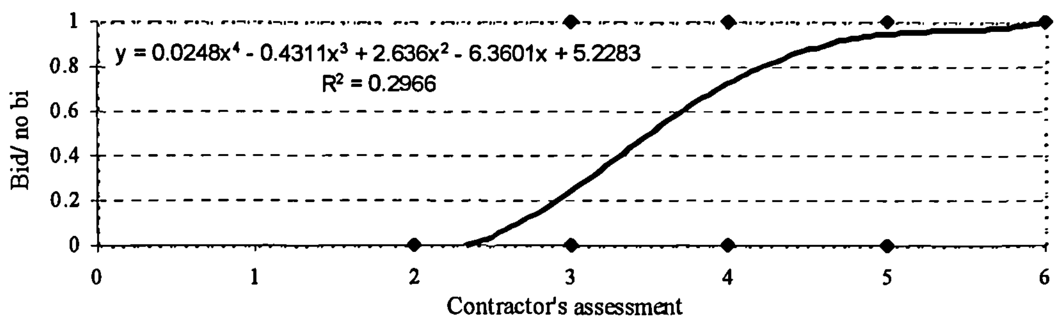



Fig. 4.20: Relationship between bid/no bid decision and availability of materials

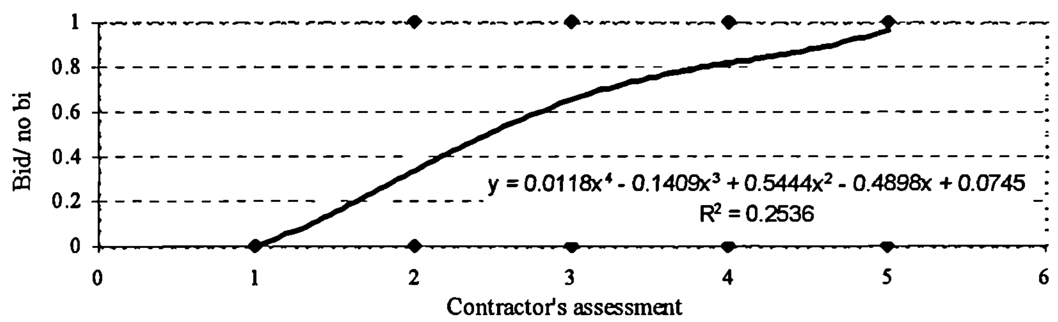



Fig. 4.21: Relationship between bid/no bid decision and proportions can be constructed mechanically

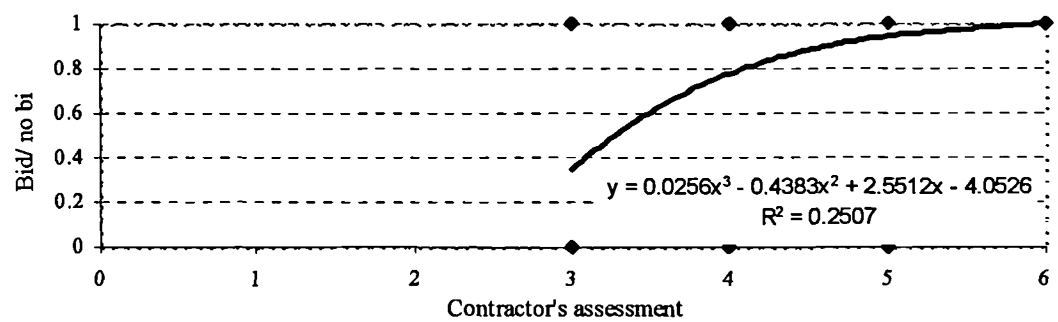



Fig. 4.22: Relationship between bid/no bid decision and confidence in the cost estimate

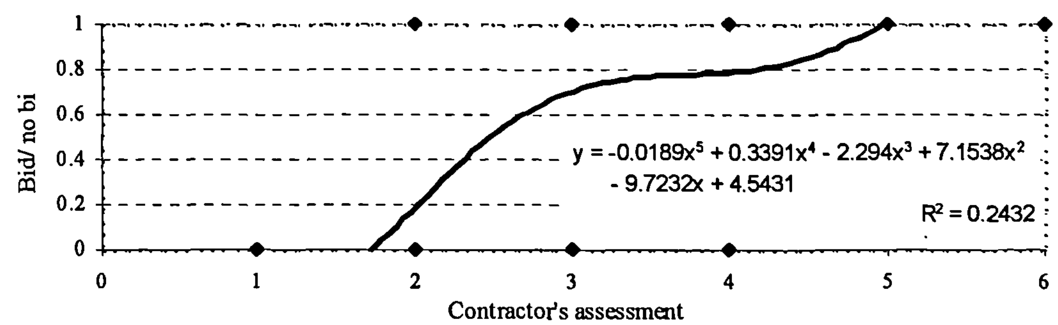



Fig. 4.23: Relationship between bid/no bid decision and financial capability of the client

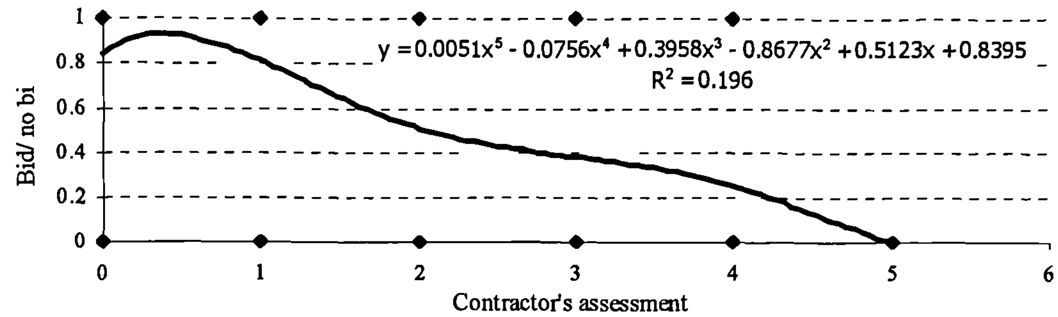



Fig.4.24: Relationship between bid/no bid decision and public objection

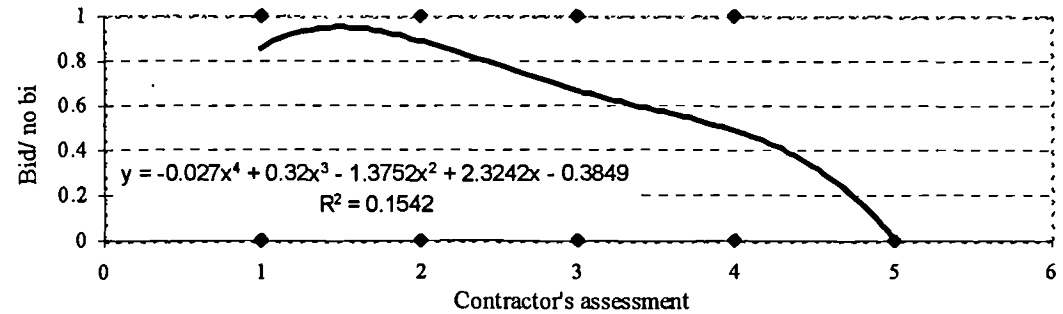



Fig. 4.25: Relationship between bid/no bid decision and current workload

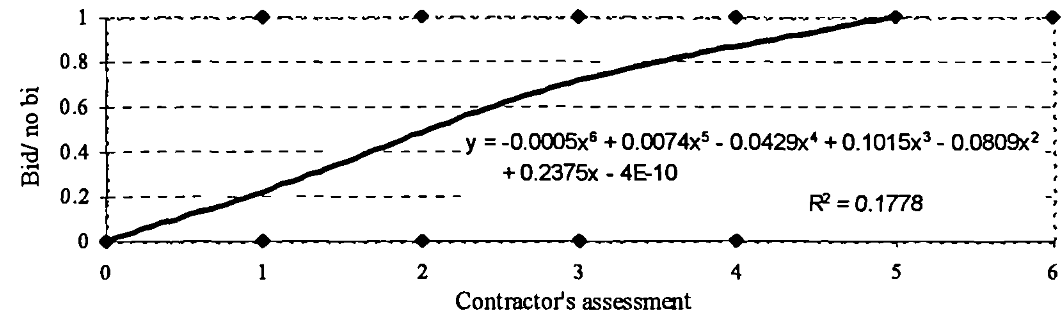



Fig. 4.26: Relationship between bid/no bid decision and relation with/ r reputation of the client

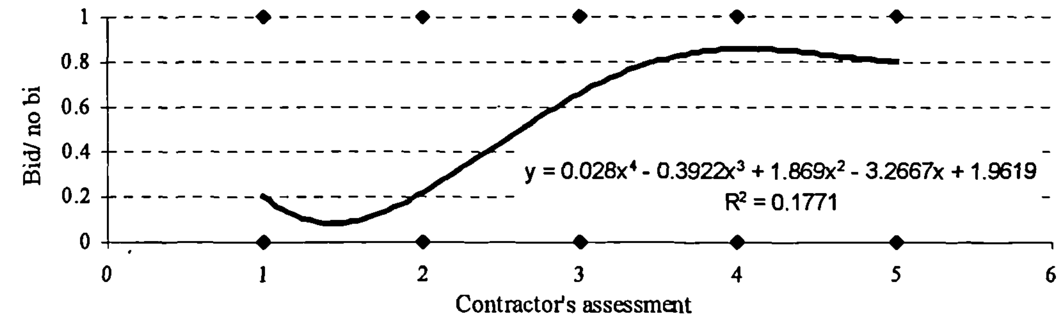



Fig. 4.27: Relationship between bid/no bid decision and favourability of the expected cash flow

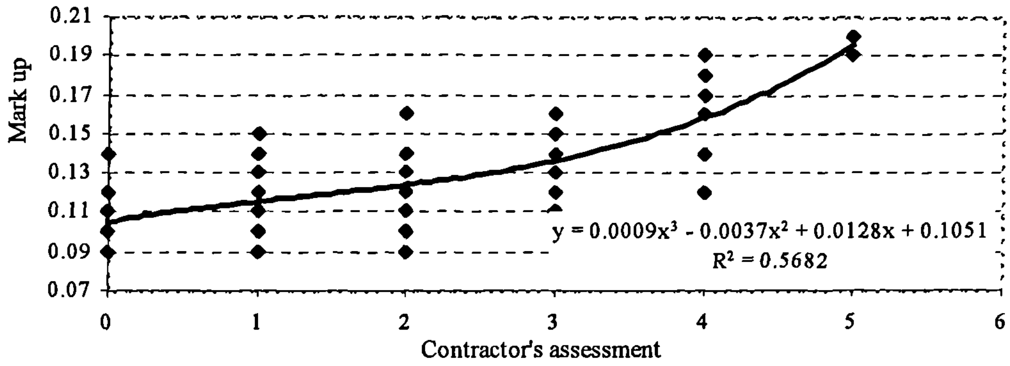



Fig. 4.28: Relationship between mark up and the expected risks

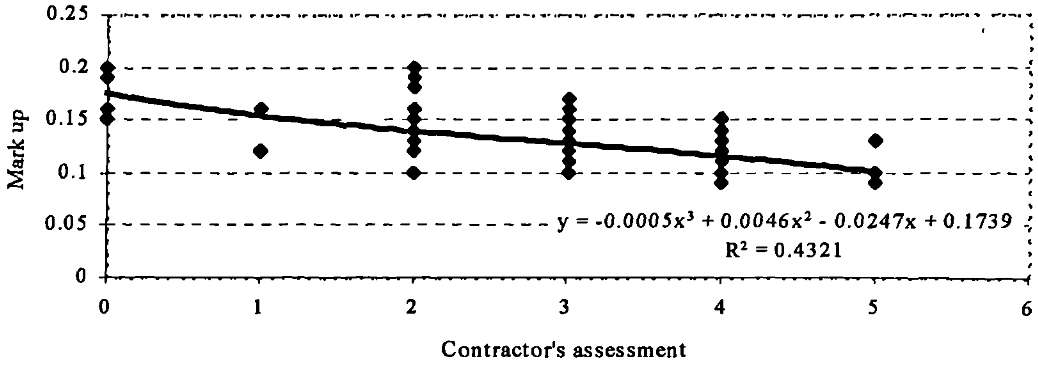



Fig. 4.29: Relationship between mark up and equipment owned

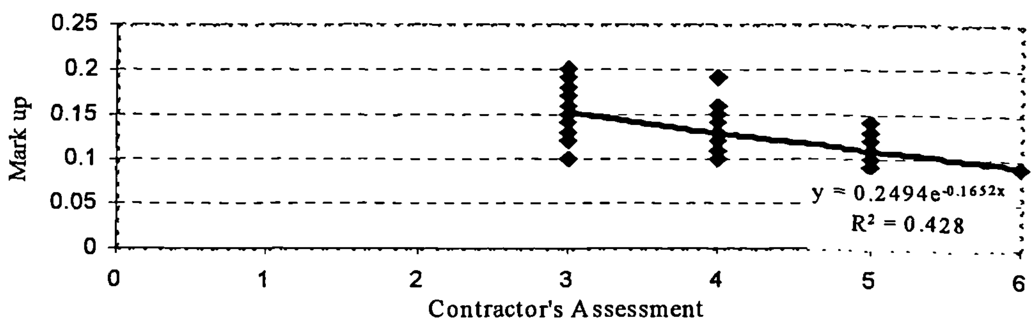



Fig. 4.30: Relationship between mark up and confidence in the cost estimate

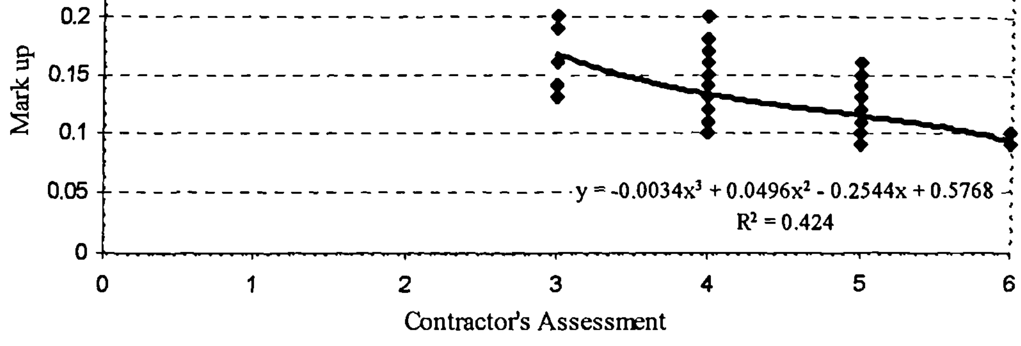



Fig. 4.31: Relationship between mark up and availability of required materials

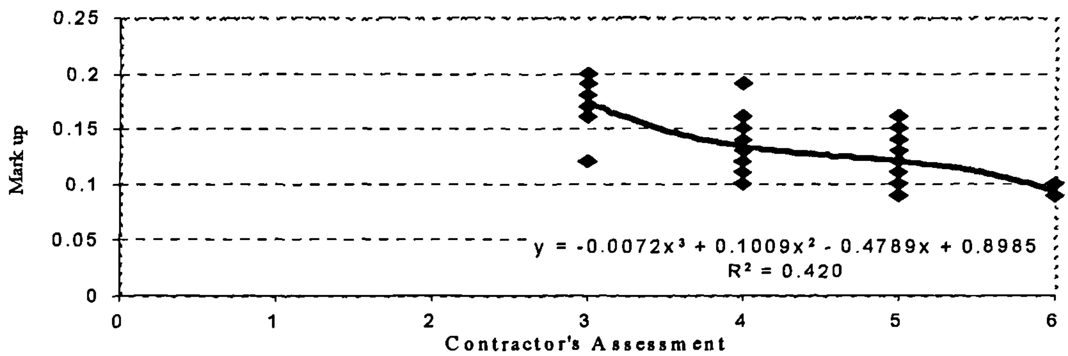



Fig. 4.32: Relationship between mark up and competence of the expected competitors

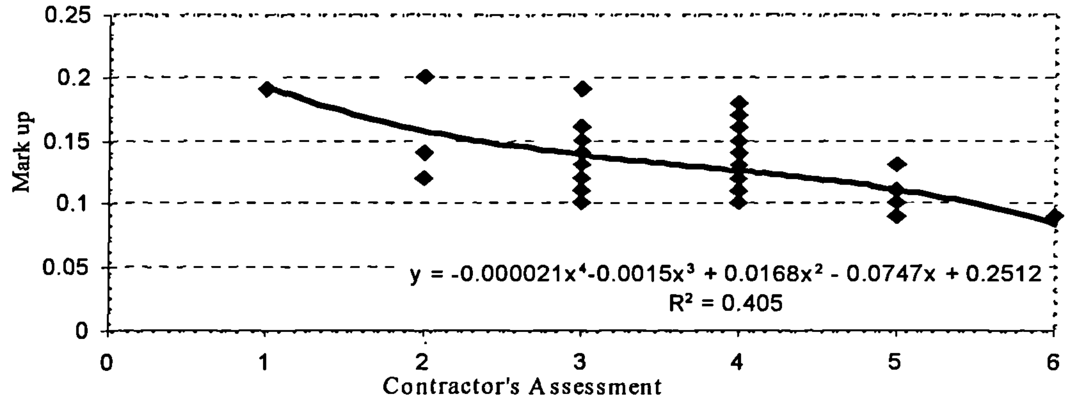



Fig. 4.33: Relationship between mark up and degree of buildability

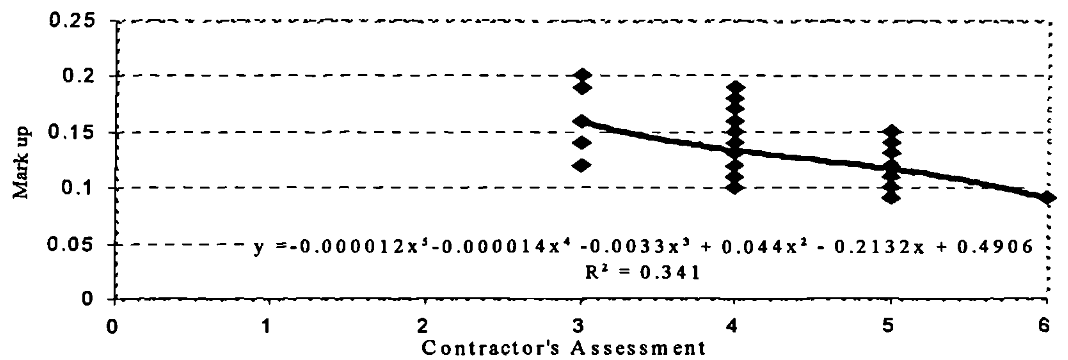



Fig. 4.34: Relationship between mark up and competition

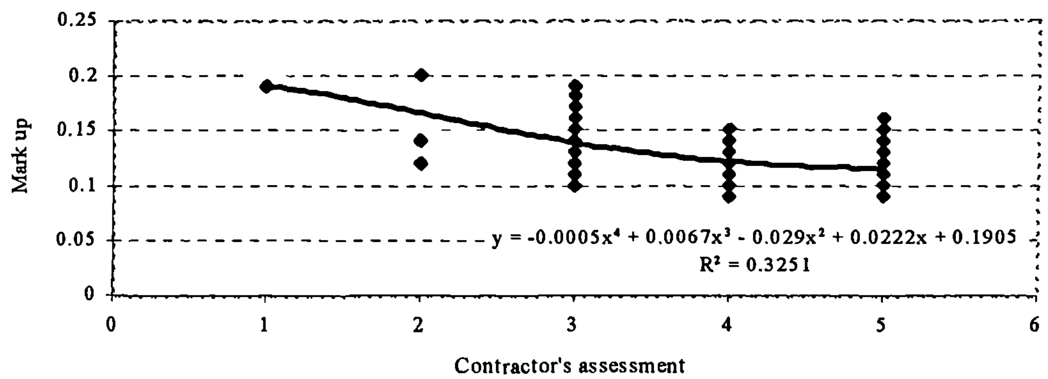



Fig. 4.35: Relationship between mark up and proportions that can be constructed mechanically

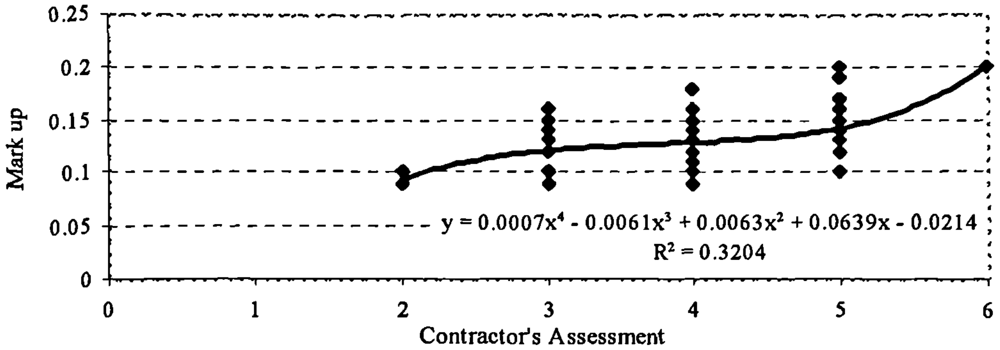



Fig. 4.36: Relationship between mark up and rigidity of specifications

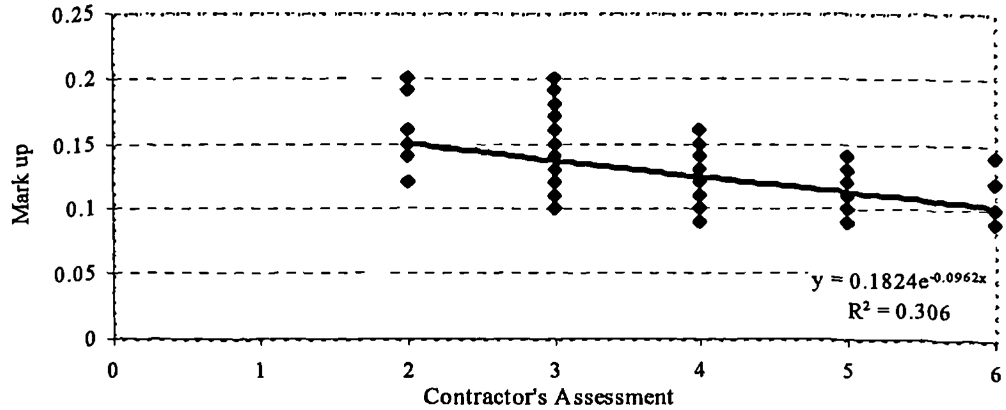



Fig. 4.37: Relationship between mark up and site clearance of obstructions

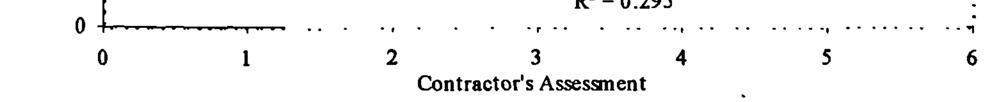



Fig. 4.38: Relationship between mark up and site accessibility

The trends presented in the current section represent the general characteristics of the bidding process in Syria. Some of these trends are similar in other countries including Canada and the USA as reported by Hegazy and Moselhi (1995). In general, the results of the presented cause-effect analysis support the validity of the collected data and subsequently increase confidence in the bidding models developed in the following chapters. The main findings of the current chapter are summarised in the following section.

## 4.17 Summary

The current chapter has started with providing a brief theoretical review of the main data collection techniques available in the literature. Semi-structured interviews and formal surveys provided to be suitable techniques to elicit the data requirements of the present study. Six sime-structured interviews were conducted among general contractors with considerable experience in the Syrian construction industry. The main findings of the interviews are:

1. A brief description of the main tendering procedures used in Syria and a general explanation of how the bidding decisions are made in practice;
2. Identifying some critical factors that can individually cause a "no bid" decision and setting a kill-score for each one of them. For example, a "no bid" decision should be made if the "fulfilment of the to-tender conditions" factor was scored less than 5, i.e. very high;

It was found that fulfilment of the to-tender conditions imposed by the client is the most important among 38 factors that affect the "bid/ no bid" decision. It has been given a very high importance (89.88%) but not 100% presumably because a contractor who does not fully meet the required conditions can submit a tender in a partnership with other contractors who do fulfil these conditions.

Availability of the required capital was ranked the sixth with a high importance (68.33%), which is less than expected perhaps because contractors can borrow the capital they require until they receive the first payment from the client. That will affect, to some extend, their mark up. On the other hand a moderate importance was assigned to the expected risks, which have more effect on the "mark up size" decision. Surprisingly the project location was assessed as a very low important factor in the bidding decision. Very little importance was assigned to competition. Number of competitors and competence of the expected competitors were ranked thirty second and thirty sixth respectively. Fluctuation in labour/materials' prices has little effect on "bid/ no bid" decision because labour/ materials' prices are currently very stable in Syria. It is worth noting that the same aforementioned factors affect the mark up size decision but to different degrees. For example risks expected, which is the eighteenth bidding criterion was ranked the first amongst thirty eight factors that affect the mark up decision. The results of the analysis were also compared with past research work on competitive bidding to validate and confirm the findings.

# CHAPTER 5
# A PARAMETRIC REGRESSION BIDDING STRATEGY MODEL

## 5.1 Introduction

The way in which the construction companies/contractors make their bidding decisions ("bid/no bid" and "mark up size") is a highly complex process. In the absence of a universal model, these decisions are often based on heuristic techniques, i.e. experience, subjective judgement and intuition of the decision maker, (Ahmad; 1990, Hegazy; 1994, Dawood; 1995). However, making the right bidding decisions is not an easy task even for highly experienced contractors. Therefore, developing an effective decision-support model for bidding in construction can yield significant benefits especially to contractors who do not have considerable experience in this domain. During the last fifty years, numerous attempts have been made to model the bidding process. Most of these attempts emphasized the second part of the process (mark up) and neglected the important first part ("bid/no bid") of the process. This chapter explains the development process of an integrated bidding strategy model that can help in making both bidding decisions. A novel technique called the Parametric Process was used in modelling the "bid/no bid" decision-making process. The regression analysis technique was used to model the mark up part of the bidding process. The methodology adopted is explained in the following section.

## 5.2 The Modelling Methodology

The literature contains many well-established techniques that have been applied to the problem of mark up. Some of these techniques proved to be useful tools for modelling this part of the bidding process, e.g. regression techniques (Broemser 1968), neural network (Moselhi et al, 1991; Hegazy 1994), and fuzzy set theory (Al-Faiyk 1996).

Unlike the neural network and the fuzzy set approaches, regression techniques can produce models that any contractor can use, i.e. skills in running complicated software are not required. Therefore, it was decided to first investigate the applicability of this technique to the mark up process. However, the literature lacks similar approved techniques for modelling the "bid/no bid" part of the bidding problem. The practical experience of the author in the Syrian construction industry enabled him to develop a new technique for this task. This technique is called the parametric process. This process was used successfully to develop an innovative parametric model that can help in making the "bid/no bid" decision.

The methodology adopted in the development process is illustrated in Fig. 5.1, which shows that the modelling procedure was carried out in the following steps:

1. Identification of the important criteria that characterise both of the bidding decisions (Bid/no bid and mark up) in the Syrian construction industry.
2. Development of a new parametric bid/no bid model. The findings of the first questionnaire (A) and the interviews were used in developing this model which was optimised using the modelling sample of the real bidding cases (162 cases out of 182 cases). The other twenty cases were left for the testing and validating process.
    - Selection of the most important bid/no bid factors (see sections 4.13, 4.14).
    - Classification of these factors into two sets; positive factors and negative factors.
    - Development of a parametric profile for each of the considered factors to compute their contribution in the "Bid" decision.
    - Creation of a Bidding Index (BI) for a certain construction project. This index is used for recommending whether to bid or not for the project under consideration.
3. Development of regression mark up model. In this stage, the incomplete seventy one cases of the real-life bidding situations were discarded. The actual mark up was not provided in these cases presumably for confidentiality reasons.

    The remaining one hundred and eleven successful cases were divided into two samples; the modelling sample (96 projects) and testing sample (15 projects).
    - Select the input factors, i.e. the most influential mark up factors. Data of the modelling sample was used in performing this step. A simple correlation analysis was carried out to identify and select only those factors that have high Correlation with the actual mark up percentage in the modelling sample (see section 4.16.3).

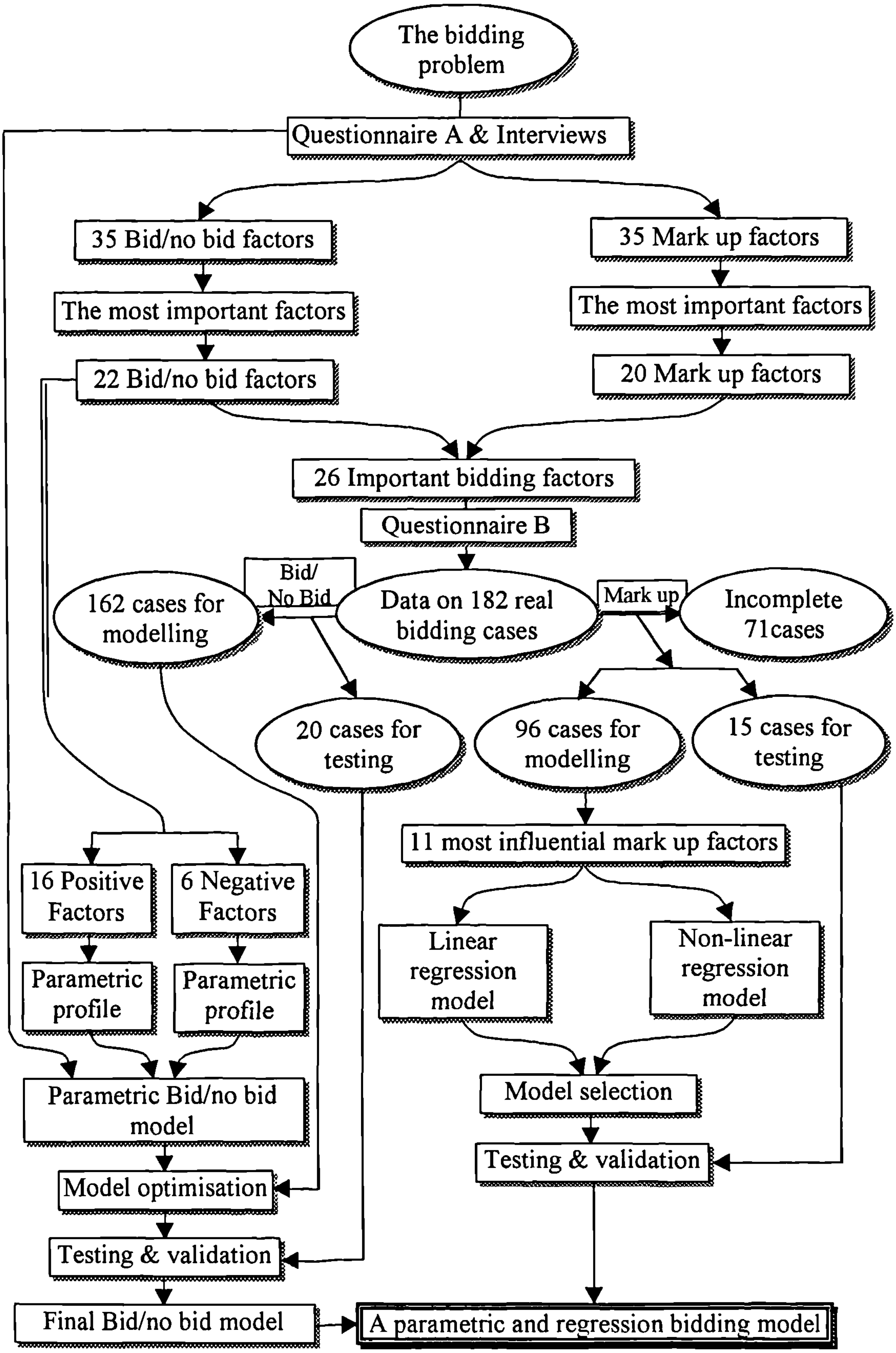



Fig. 5.1 Development methodology of a parametric and regression bidding strategy model

- Use of the SPSS statistical package to find the optimum multiple linear regression equation that simulates the mark up selection in the modelling sample.
- The establishment of the non-linear regression equation that best fitted the modelling sample.
- Select the best regression model in terms of how well it fits the modelling sample and how accurate it is in simulating the actual mark ups of the testing sample.

4. Integration of the final bid/no bid and mark up models into one parametric and regression bidding strategy model.

### 5.3 Bid/No Bid Development

The factors that influence the "bid/no bid" decision making process in the Syrian construction industry were identified in Chapter 4. The following sections explains how the most influential factors were selected and classified and how a parametric profile was assigned to each one to develop an innovative model to help contractors in making their "bid/no bid" decisions.

#### 5.3.1 Selection of the Input Variables

Chapter 4 explained how the factors that characterise the bidding process in the Syrian construction industry were identified and ranked according to their importance in making both the "bid/no bid" and the mark up decisions. Table 4.5 contains a list of thirty eight factors, each with its index of importance in making the "bid/no bid" decision. These factors were classified into two groups. Group one contains factors whose high scores usually encourage the "bid" decision (see Table 4.6). On the other hand, group two contains factors whose high scores usually discourage the "bid" decision (see Table 4.7).
Factors included in group one are called "positive factors" whilst, factors in group two are called "negative factors". This classification of the bidding factors into these two groups is artificial and simply indicates that an increasing score in a positive

factor strengths the "Bid" recommendation whilst the opposite is true for a negative factor. Depending on the scores assigned in particular case, a negative factor may still have a positive effect on the "Bid" recommendation. Also, a positive factor may have a negative effect in a particular case (refer to Fig. 5.4 and Fig. 5.6). Correlation analysis performed on one hundred and sixty two real bidding situations confirmed that positive factors have positive correlation with the actual bidding decision. Whilst, the negative factors have negative correlation with this decision (refer to Table 4.8).

Nonetheless, it is acknowledged that this classification might not be true in all cases as high scores of some negative factors could be considered by some contractors in certain bidding circumstances as encouraging and vice versa. Also, it is worth mentioning that the subjective assessments of bidding situations will be influenced by the bidder's attitude towards risk and uncertainty.

Some factors were ignored as they have little effect on the "bid/no bid" decision (see section 4.11). The remaining positive factors are listed in Table 5.1, each ($F_i$) with the following parameters:

- ($Ib_i$): index of importance in making the bid/no bid decision (see section 4.11);
- ($B_i$): a neutral score above which ($F_i$) will have a positive effect on the "bid" decision (see section 4.13); and,
- ($NB_i$): a "kill" score below which the factor will be enough to cause a "no bid" decision (see section 4.7).

Table 5.1: Parameters of the positive bidding factors

| $i$ | **Positive Bidding Factors** | **Ib** (%) | **$B_i$** Sta. Dev. | Mean | **$NB_i$** |
|---|---|---|---|---|---|
| 1. | Fulfilling the to-tender conditions imposed By the client | 90 | 0.37 | 5.84 | 5 |
| 2. | Financial capability of the client | 78 | 0.88 | 3.48 | 2 |
| 3. | Relations with and reputation of the client | 77 | 0.73 | 3.84 | 2 |
| 4. | Availability of time for tendering | 71 | 1.09 | 2.54 | 0 |
| 5. | Availability of capital required | 68 | 0.73 | 3.41 | 2 |
| 6. | Site clearance of obstructions | 68 | 0.90 | 3.64 | 0 |
| 7. | Availability of materials required | 66 | 0.90 | 3.56 | 2 |
| 8. | Experience in similar projects | 64 | 0.74 | 3.61 | 2 |
| 9. | Availability of equipment required | 64 | 0.84 | 3.40 | 0 |
| 10. | Method of construction (manually, mechanically) | 64 | 0.72 | 3.05 | 0 |
| 11. | Availability of skilled labour | 58 | 0.83 | 3.25 | 0 |
| 12. | Original project duration | 56 | 0.79 | 3.02 | 0 |
| 13. | Site accessibility | 54 | 1.03 | 3.00 | 0 |
| 14. | Favourability of the expected cash flow | 47 | 1.08 | 2.80 | 0 |
| 15. | Degree of buildability | 47 | 1.11 | 2.28 | 0 |
| 16. | Confidence in the cost estimate | 45 | 0.73 | 3.85 | 0 |

The considered negative factors are listed in Table 5.2, each ($F_j$) with the following parameters:

- ($Ib_j$): index of importance in making the bid/no bid decision(see section 4.5.1.5);
- ($B_j$): a neutral score above which ($F_j$) will have a positive effect on the "bid" decision (see section 4.5.1.7); and,
- ($NB_j$): a "kill" score below which the factor will be enough to cause "no bid" decision (see section 4.4.2).

Table 5.2: Parameters of the negative bidding factors

| $j$ | **Negative Bidding Factors** | **Ib** (%) | **$B_j$** Sta. Dev. | Mean | **$NB_j$** |
|---|---|---|---|---|---|
| 1. | Project size | 73 | 0.65 | 3.69 | 5 |
| 2. | Public objection | 68 | 0.75 | 2.15 | 4 |
| 3. | Current workload | 66 | 0.75 | 2.90 | 6 |
| 4. | Risks expected | 52 | 0.73 | 3.12 | 6 |
| 5. | Rigidity of specifications | 50 | 0.75 | 3.66 | 6 |
| 6. | Availability of other projects | 46 | 0.76 | 5.21 | 6 |

Some features of the Syrian construction industry are reflected in the $B_i$, $NB_i$, $B_j$, and $NB_j$ values. Therefore, this model might be of greater help to new contractors who do not have considerable experience in dealing with new bidding situations. However, experienced contractors can modify these values to suit their own bidding policies.

### 5.3.2 Development of a Bidding Index

The developed model will recommend whether to bid on a new project or not based on an index called the " Bidding Index" (BI) produced for this project. The following explains the development of the BI.

A parametric scale was developed for each bidding factor ($F_i$ and $F_j$ in Tables 5.1 and 5.2). Fig. 5.3 illustrates the general structure of a parametric scale of a positive factor.

Factor $F_i$ is represented in Fig. 5.2 as a beam, with a length of zero to six and supported on the neutral point ($B_i$) which is considered to be the centre of gravity of this beam. Without applying any force, this beam will stay horizontal.

A contractor can assess a new bidding situation in term of factor $F_i$ by subjectively assigning a score $CA_i$ (Contractor's Assessment) between zero and six. The contractor's assessment is presented in Fig. 5.3 as a force applied at the $CA_i$ point. The magnitude of this artificial force represents how important the factor $F_i$ is in making the "bid/no bid" decision, i.e. it is equal to the importance index ($Ib_i$).

Applying this force will generate a moment, which is the physical representation of the contribution ($CB_i$) of factor $F_i$ in making the "bid" decision.

Based on these assumptions, the following formula is used to compute the contribution ($CB_i$) of a positive factor ($F_i$):

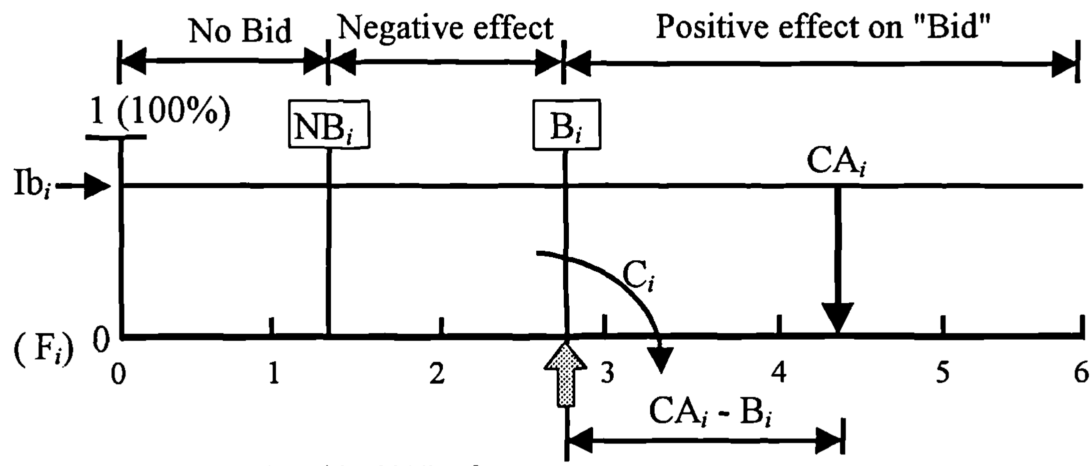
$$CB_i = Ib_i * (CA_i - B_i) \qquad (5.1)$$

For example, the importance of "Availability of materials required" factor in making the "bid/no bid" decision is (Ib = 0.66) and its neutral score is (B = 3.56). If this factor is rated as "low", i.e. CA=2", in a certain bidding situation, the contribution in the "bid" decision can be computed using formula 5.1 as follows:

CB = 0.66 * (2-3.56)

CB = -1.03

This value of contribution means that the "availability of materials required" factor does not encourage the "bid" decision. If the contractor's assessment was "extremely high", i.e. CA = 6, the contribution will be (CB = +1.61), which encourages the "bid" decision.




$F_i$: A positive bidding factor;
$Ib_i$: Importance in making the "bid/no bid" decision;
$NB_i$: Kill-score of factor $F_i$;
$B_i$: Neutral score for factor $F_i$; and,
$CA_i$: Contractor's assessment of the bidding situation regarding Factor $F_i$.

Fig. 5.2: A parametric model for a positive factor

The influence of the "availability of materials required" factor on the "bid" recommendation is presented graphically in Fig. 5.3 as an example to clarify the effect of the so called "positive" factors. It is clear that this "positive" factor still has a negative effect if the contractor's assessment was CA< 3.56 (the neutral score) and that it will cause a "no bid" recommendation when CA< 2 (the "kill" score).

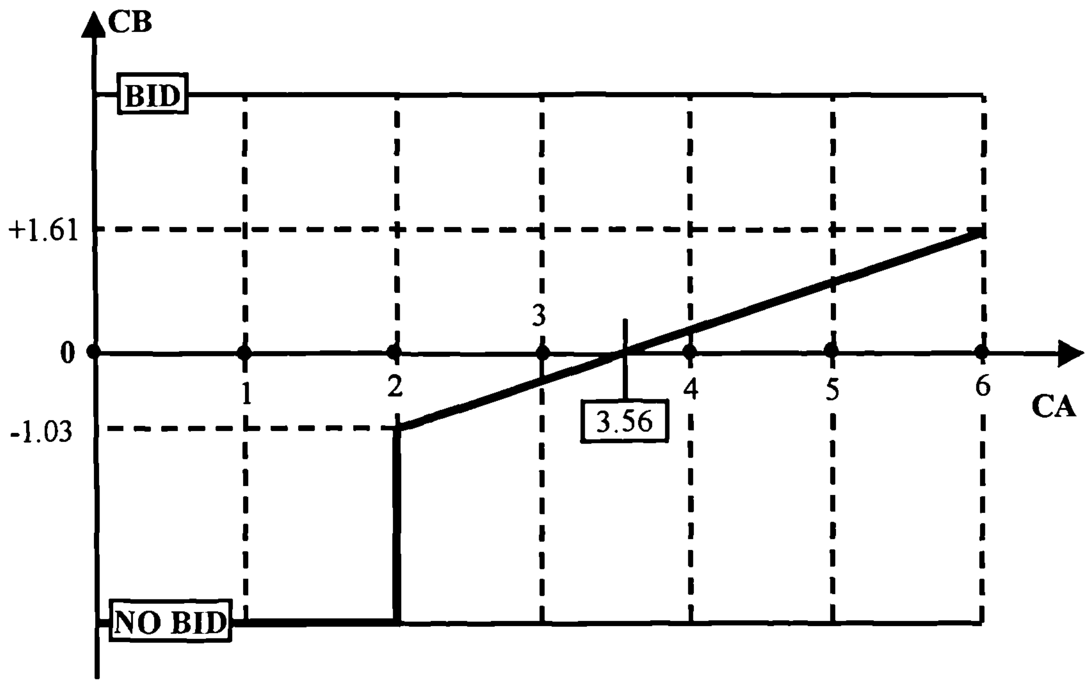
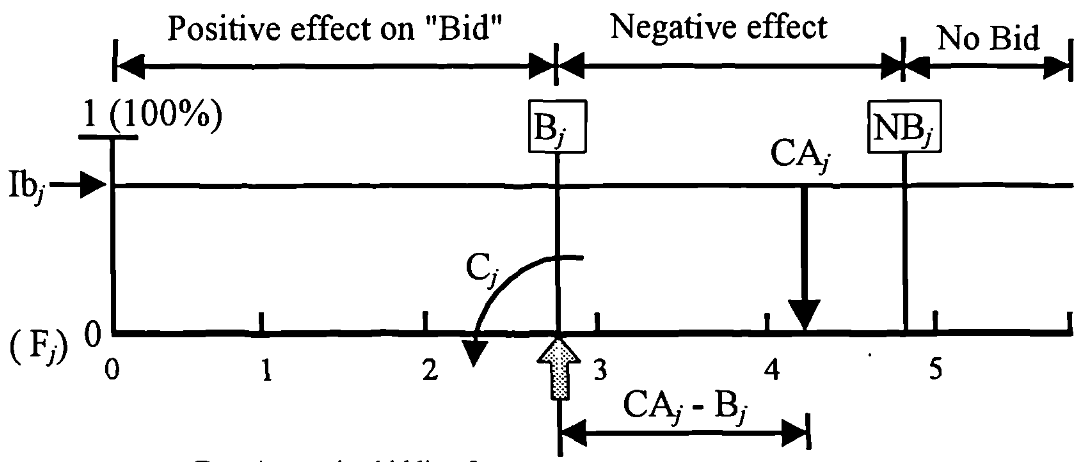



Fig. 5.3: Contribution of "availability of materials" factor in the "Bid" recommendation

Similarly, Fig. 5.4 illustrates the general structure of a parametric scale of a negative factor $F_j$. In the case of a negative factor, a contractor's assessment ($CA_j$) that is higher than the neutral score ($B_j$) will generate a negative contribution in making the "bid" decision. Thus, the following formula is used to compute the contribution of a negative factor in the "bid" decision ($CB_j$):

$$CB_j = - Ib_j * (CA_j - B_j) \qquad (5.2)$$

The influence of the "Public objection" factor is illustrated in Fig. 5.5 as an example of the so classified "negative" factors. This figure shows that the "Public objection" factor still has a positive effect when CA< 2.15 (the neutral score).




$F_j$: A negative bidding factor;
$Ib_j$: Importance in making the "bid/no bid" decision;
$NB_j$: Kill-score of factor $F_j$;
$B_j$: Neutral score for factor $F_i$; and,
$CA_j$: Contractor's assessment of the bidding situation regarding Factors $F_j$.

Fig. 5.4: A parametric model for a negative factor

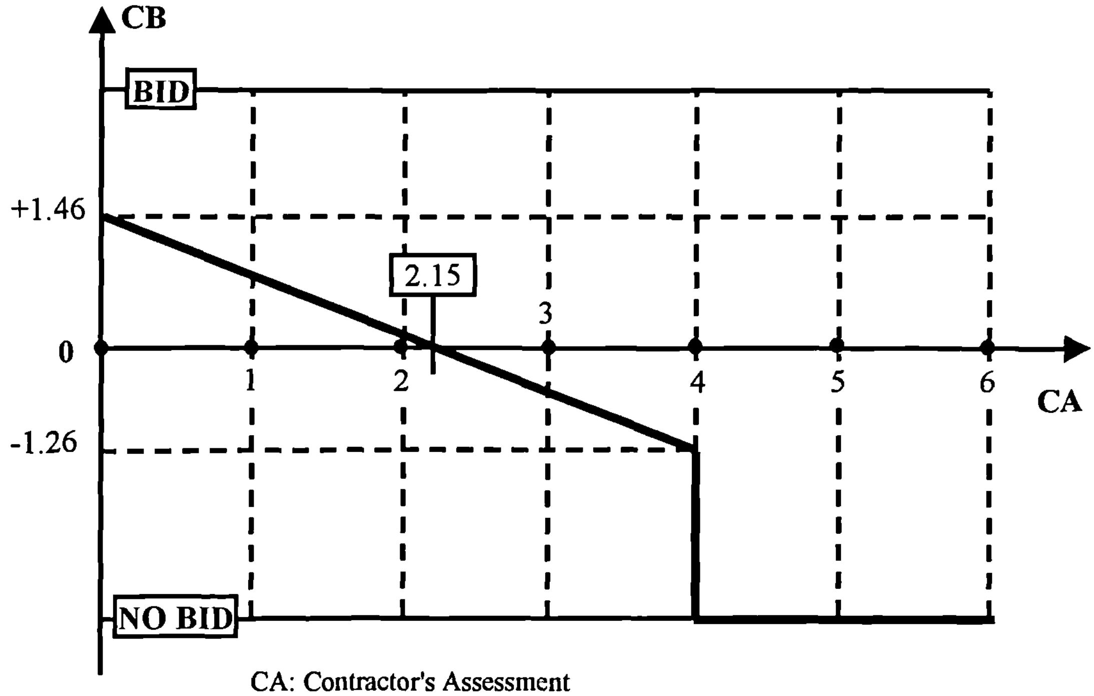
The cumulative contribution of all the considered bidding factors in making the "bid" decision is the bidding index (BI) that is computed for a new project ($k$) using the following formula:

$$BI_k = \sum_{i=1}^{m} Ib_i * (CA_i - B_i) - \sum_{j=1}^{n} Ib_j * (CA_j - B_j) \qquad (5.3)$$

Where:

m: number of the considered positive factors; and,

n: number of the considered negative factors.




CA: Contractor's Assessment
CB: Contribution to the "Bid" recommendation

Fig 5.5: Contribution of " Public objection" factor in the "bid" recommendation

$BI_k$ indicates the degree of desirability of bidding on the project (k). The additivity adopted in formula (5.3) is justified by the small correlation between bidding attributes, i.e. they can be considered as independent attributes, (refer to section 9.4.1.1.1). This additivity, also, has been defended by others (Ahmad 1990) by considering the following points:

1. In most circumstances, a bidder treats the factors independently.
2. The independence assumption allows the model to be kept simple to understand and easy to use.
3. Although, in a strict theoretical sense, this assumption may not be truly realistic, it serves the purpose of rational decision-making.
4. It may equally be questioned that a complex model allowing dependency would yield better decisions.

The bidding index (BI) of a new project represents a mixture of the following aspects:

1- The suitability of the project in terms of experience available, financial capability, etc.

2- The company's need for work.
3- The desirability of working with the client.
4- The prevailing market conditions in terms of availability of other projects, plant and labour, and availability of the required materials.

The process of computing the bidding index of a new bidding situation is illustrated in Fig. 5.6 and explained in section 5.3.3.

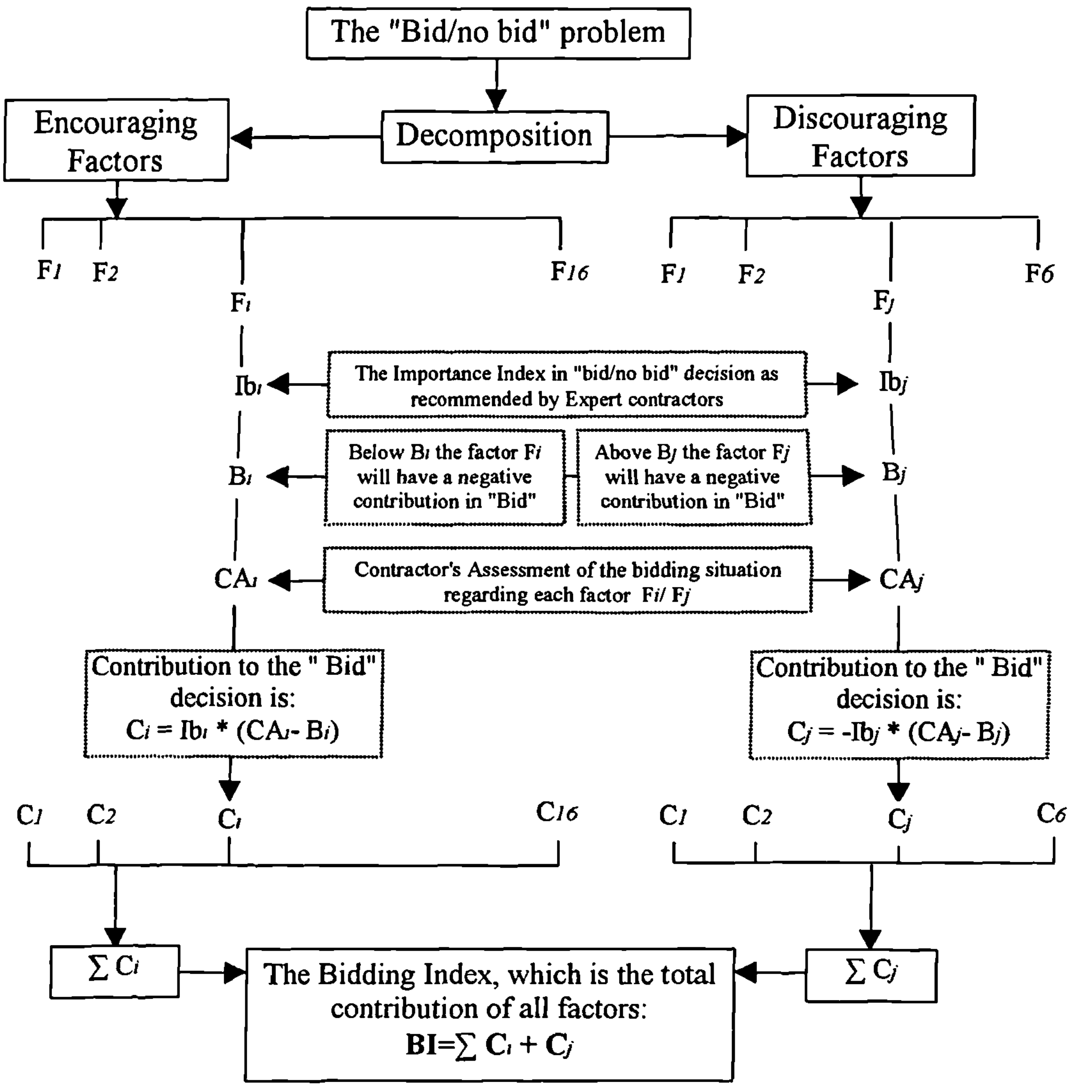



Fig 5.6: Production of the bidding index (BI)

### 5.3.3 A Parametric Bid/No Bid Model

In the previous section, an index on which the developed model will base its recommendation was introduced. For $CA_i = B_i$ and $CA_j = B_j$, the bidding index will be $BI_k = 0$. That represents the mid-point case scenario where there are neither positive nor negative effects on the "Bid" decision, i.e. the strengths of both "Bid" and "No Bid" decisions are equal.

If $BI_k > 0$, that indicates a more positive effect on the "bid" decision. Thus, the model will recommend the "bid" decision when $BI_k \geq 0$ and the "no bid" decision when $BI_k < 0$.

Still there is an important point that needs to be considered. That is, in some situations, individual factors can cause a "no bid" recommendation no matter what the contributions of the other factors are. For instance, if a contractor does not have any experience in projects of the type and size being considered, the "no bid" recommendation should be made. This is taken into account in the developed model by introducing the "kill" score parameter ($NB_i$ or $NB_j$). Before computing the contribution of a certain factor, the contractor's assessment is compared to the kill score of this factor. In case of any violation, the "no bid" recommendation is made.

Fig. 5.7 illustrate the conditions adopted in this model when recommending whether to bid or not on a new project.

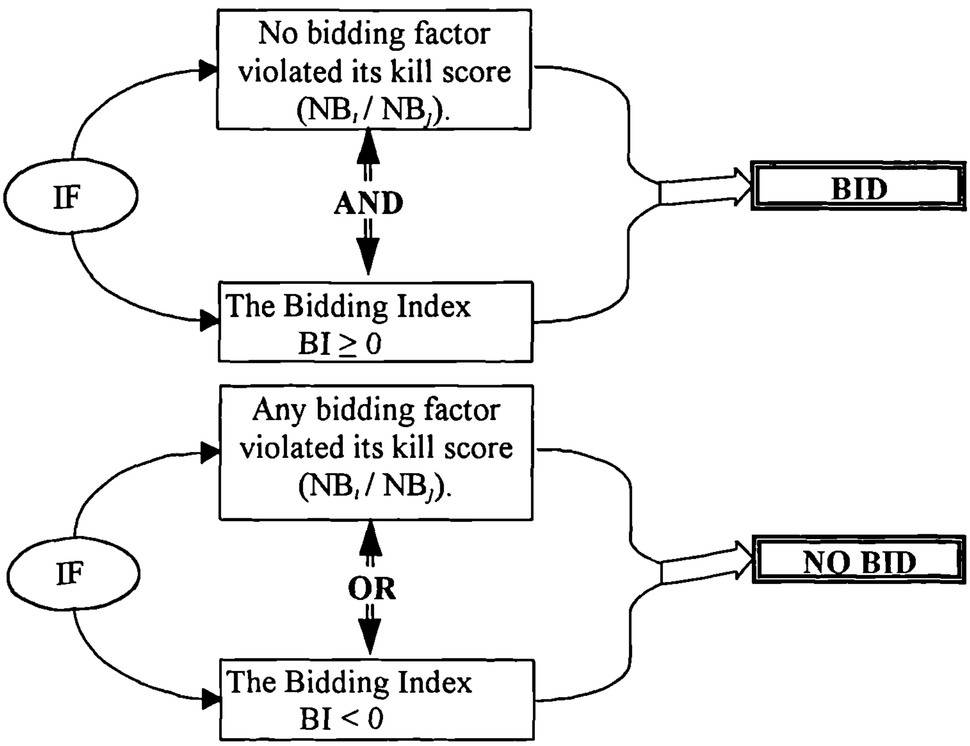



Fig.5.7: Bid or no bid conditions

The final condition considered in this model is the availability of capital that can be devoted to the new project under consideration. According to the findings of questionnaire A, the minimum capital required to start a new construction project (k) is given in the following formula (see section 4.5.1.4/3):

$$MRC_k = 0.21 * PS_k \qquad (5.4)$$

Where:

$MRC_k$: Minimum required capital for a new project (k); and,

$PS_k$: Project size.

The overall structure of the developed model is illustrated graphically in Fig. 5.8 and can be explained as follows:

1- Considering a new project (k), the user is requested to input the project size ($PS_k$). As recommended by the Syrian contractors, the minimum required capital is: $MRC_k = 0.21 * PS_k$. That will be compared to the actual available capital ($AC_k$) that is provided by the user as another input. In the case of $AC_k < MRC_k$, the "no bid" decision is recommended. The contractor has the option to accept or reject this recommendation. This is because a contractor may choose to borrow some capital till he receives a payment from the client.

2- If the contractor decided to proceed (or $AC_k > MRC_k$), he will be requested to describe the bidding situation by assigning subjectively a suitable score between 0 ( extremely low) and 6 ( extremely high) to each positive factor. In the case of any one of these factors violating its kill value, the "no bid" decision is recommended. This decision may be accepted or rejected by the user.

3- Step 2 repeated for the negative factors.

4- Having all the required inputs, the model produces the Bidding Index ($BI_k$).

5- If $BI_k \geq 0$ then the "bid" decision is recommended.
If $BI_k < 0$ then the "no bid" decision is recommended.

6- Steps 1-5 can be repeated for other new projects or for what-if analysis on a single project.

7- All the projects examined in a session are ranked in descending order according of the bidding index. This indicates which project is most suitable for the user.

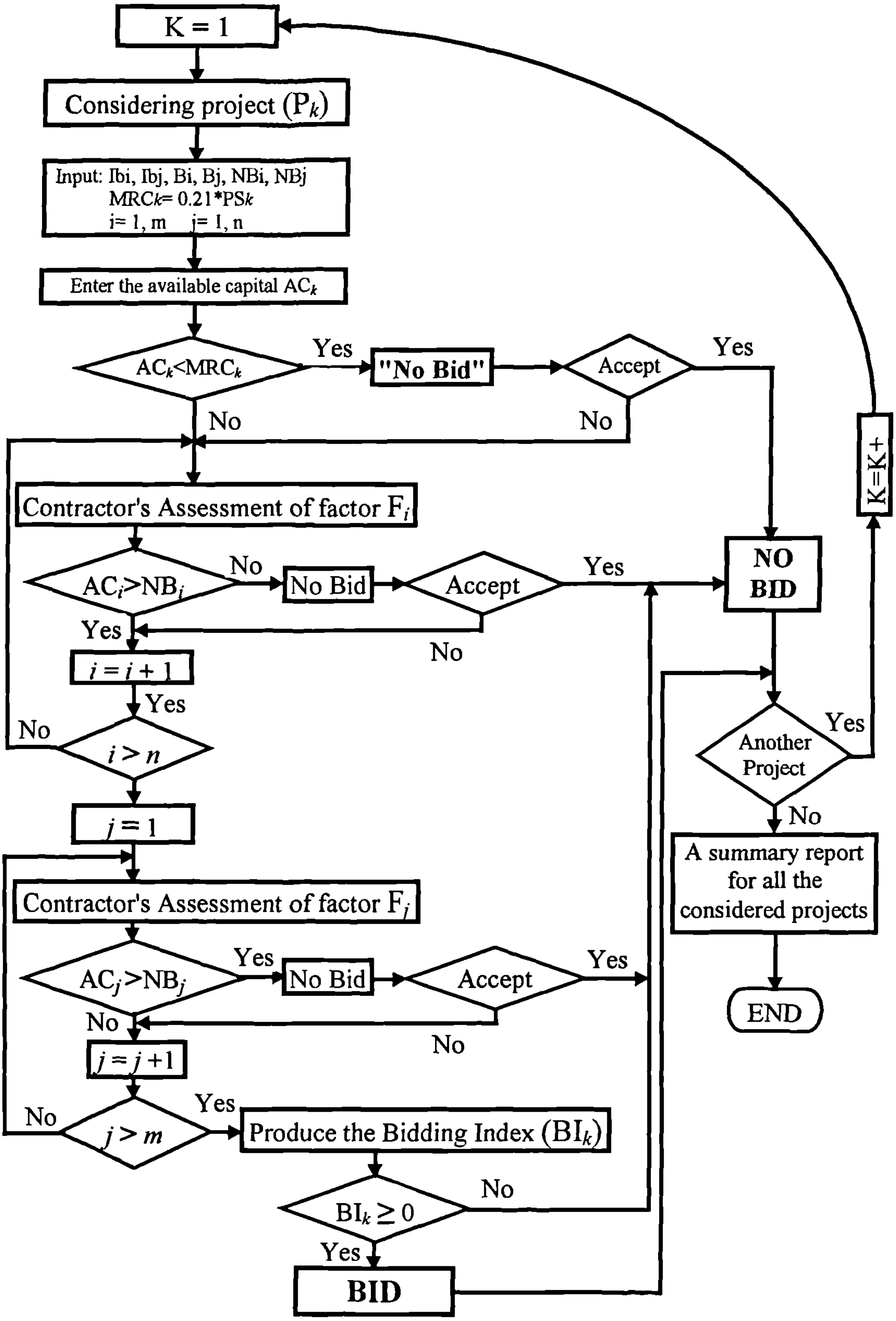



Fig. 5.8: A flowchart model for "Bid/no bid" decision

### 5.3.3.1 Sensitivity Analyses

An attempt was made to simplify the developed bidding model by reducing the number of inputs required. This was done without affecting the model accuracy significantly. One hundred and sixty two real-life bidding cases, collected through questionnaire B were used in a series of tests in which various factors were omitted from the model. These real cases were also used to optimise the developed model and to complement it with a confidence degree model as described in the following two sections. The remaining twenty cases were used in testing and validating the final optimised model.

Theoretically, the least important factors should be considered for omission first. However, this strategy could be invalid because the importance degrees of the bidding factors in real situations might differ from these suggested by contractors. Also, besides the importance index (Ib), there are other parameters ($B_i$ and $B_j$) that affect the bidding index (BI).

To overcome this problem, a sensitivity index was developed for each bidding factor. For each factor, three values of the bidding index (BI0, BI3 and BI6) were produced for three values of the contractor's assessment (AC=0, 3 and 6), while setting the other factors to the mid-case scenario, i.e. $CA_i = B_i$ and $CA_j = B_j$, where BI=0.

A sensitivity index (SI) of a bidding factor is defined by the following equation:

$$SI = |BI0 - BI6| \qquad (5.5)$$

Table 5.3 represents BI0, BI3, BI6 and SI of all the considered bidding factors ranked in descending order of importance.

Fig. 5.9 illustrates the sensitivity of the "bid/no bid" decision to changes in individual factors.

Table 5.3: Sensitivity of the parametric model to changes in individual factors

| *i* | **Bidding Factors** | **BI (0)** | **BI (3)** | **BI (6)** | **SI $\|BI_0-BI_6\|$** |
|---|---|---|---|---|---|
| 1. | Fulfilling the to-tender conditions | -5.25 | -2.55 | +0.14 | 5.39 |
| 2. | Financial capability of the client | -2.70 | -.037 | +1.95 | 4.65 |
| 3. | Relation with/reputation of the client | -2.95 | -0.55 | +1.66 | 4.61 |
| 4. | Project size | +2.70 | +0.50 | -1.69 | 4.39 |
| 5. | Availability of time for tendering | -1.80 | +0.33 | +2.45 | 4.25 |
| 6. | Availability of capital required | -2.33 | -0.28 | +1.77 | 4.10 |
| 7. | Site clearance of obstructions | -2.48 | -0.44 | +1.60 | 4.08 |
| 8. | Public objection | +1.46 | -0.58 | -2.61 | 4.07 |
| 9. | Availability of materials required | -2.36 | -0.37 | +1.62 | 3.98 |
| 10. | Current workload | +1.91 | -0.07 | -2.04 | 3.95 |
| 11. | Experience on similar projects | -2.31 | -0.39 | +1.53 | 3.84 |
| 12. | Availability of equipment required | -2.18 | -0.26 | +1.66 | 3.84 |
| 13. | Proportion that could be constructed mechanically | -1.95 | -0.03 | +1.89 | 3.84 |
| 14. | Availability of Skilled labour | -1.89 | -0.15 | +1.60 | 3.49 |
| 15. | Sufficiency of the project duration | -1.68 | 0.00 | +1.68 | 3.36 |
| 16. | Site accessibility | -1.63 | -0.01 | +1.60 | 3.23 |
| 17. | Risks expected | +1.63 | +0.06 | -1.50 | 3.13 |
| 18. | Rigidity of specifications | +1.83 | +0.33 | -1.17 | 3.00 |
| 19. | Favourability of the expected cash flow | -1.32 | +0.09 | +1.50 | 2.82 |
| 20. | Degree of buildability | -1.07 | +0.34 | +1.75 | 2.82 |
| 21. | Availability of other projects | +2.41 | +1.02 | -0.37 | 2.78 |
| 22. | Confidence in the cost estimate | -1.75 | -0.39 | +0.98 | 2.73 |

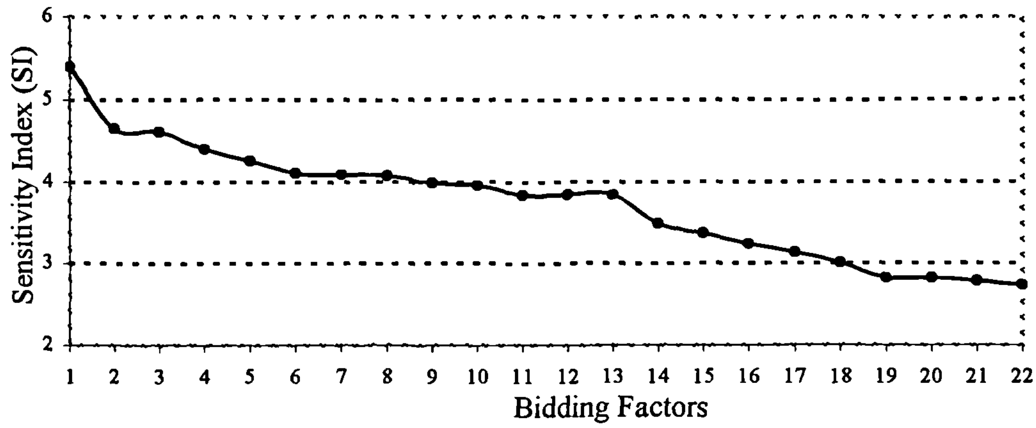



Fig. 5.9: Sensitivity of the bidding index to changes in individual factors

Factors $F_{22}$, $F_{21}$, $F_{20}$, $F_{19}$, $F_{18}$, $F_{17}$, $F_{16}$ and $F_{15}$ have the lowest SIs. The model was tested, using one hundred and sixty two real bidding situations, with factor $F_{22}$ being eliminated.

The same process was repeated for factors ($F_{22}+F_{21}$);

($F_{22}+ F_{21}+F_{20}$);

($F_{22} +F_{21}+F_{20}+F_{19}$);

$(F_{22}+F_{21}+F_{20}+F_{19}+F_{18})$;

$(F_{22}+F_{21}+F_{20}+F_{19}\ F_{18}+F_{17})$;

$(F_{22}+F_{21}+F_{20}+F_{19}+F_{18}+F_{17}+F_{16})$; and,

$(F_{22}+F_{21}+F_{20}+F_{19}+F_{18}+F_{17}+F_{16}+F_{15})$.

Table (5.4) presents the number of the miss-predicted decisions corresponding to discounting these factors.

Table 5.4: Model sensitivity to omitting some factors

| **Omitted Factors** | **Unsuccessful Predictions** |
|---|---|
| None | 16 |
| F22 | 17 |
| F22+ **F21** | 16 |
| F22+ F21 +**F20** | 15 |
| F22+ F21 +F20 +F19 | 15 |
| F22+ F21 +F20 +F19 +F18 | 16 |
| F22+ F21 +F20 +F19 +F18+**F17** | 15 |
| F22+ F21 +F20 +F19 +F18+F17+ F16 | 17 |
| F22+ F21 +F20 +F19 +F18+F17+ F16+ F15 | 18 |
| **F21+F20 +F17** | **14** |

Leaving out factor $F_{21}$, $F_{20}$ and $F_{17}$ out caused some improvement in the model accuracy in simulating the contractors' decisions. Therefore, it has been decided not to consider these factors in the final model. It is not necessary to discount other bidding factors because the user could assess them very easily. Also, it is not necessary to examine omitting different combinations of factors, i.e. $F_{22}+F_{16}$, $F_{22}+F_{17}+F_{21}$, etc., mainly because it was assumed that the bidding factors are independent, i.e. the correlation between them is negligible.

### 5.3.3.2 Model Optimisation

As explained in section 5.3.2, the bidding parameters ($I_i$, $I_j$, $B_i$, $B_j$, $NB_i$, and $NB_j$) are based on information provided by Syrian contractors through Questionnaire A supported by six semi-structured interviews (see chapter 6).

These parameters are used in addition to the contractor's assessments ($CA_i$/ $AC_j$) to produce a bidding index for a new bidding situation. This is done by applying formula 5.8.

It was believed that the proposed model could be optimised by amending the bidding index equation. One way to test this belief was by trying different values of $B_i$ and $B_j$. Initially, the "mean" value was adopted for $B_i$ and $B_j$. The model was used to predict the actual "bid/ no bid" decisions of one hundred and twenty two real bidding cases with different values of $B_i$ and $B_j$.

Table (5.5) presents different values of $B_i$ and $B_j$ along with the corresponding number of unsuccessful predictions and number/percentage of successful predictions.

Table 5.5: Selection of the best value for $B_i$ and $B_j$.

| Bi | Bj | Unsuccessful predictions | Successful predictions | |
|---|---|---|---|---|
| | | | No. | (%) |
| Mi - Si | Mj + Sj | 21 | 141 | 87.04 |
| Mi - 0.75*Si | Mj + 0.75*Sj | 20 | 142 | 87.65 |
| Mi - 0.5*Si | Mj + 0.5*Sj | 18 | 144 | 88.89 |
| Mi - 0.25*Si | Mj + 0.25*Sj | 17 | 145 | 89.51 |
| Mi | Mj | 15 | 147 | 90.74 |
| Mi + 0.25*Si | Mj - 0.25*Sj | 22 | 140 | 86.41 |
| Mi + 0.5*Si | Mj - 0.5*Sj | 33 | 129 | 79.63 |
| Mi + 0.75*Si | Mj - 0.75*Sj | 66 | 96 | 59.26 |
| Mi + Si | Mj - Sj | 90 | 72 | 44.44 |

Fig. 5.10 illustrates the process of selecting the optimum values of $B_i$ and $B_j$.

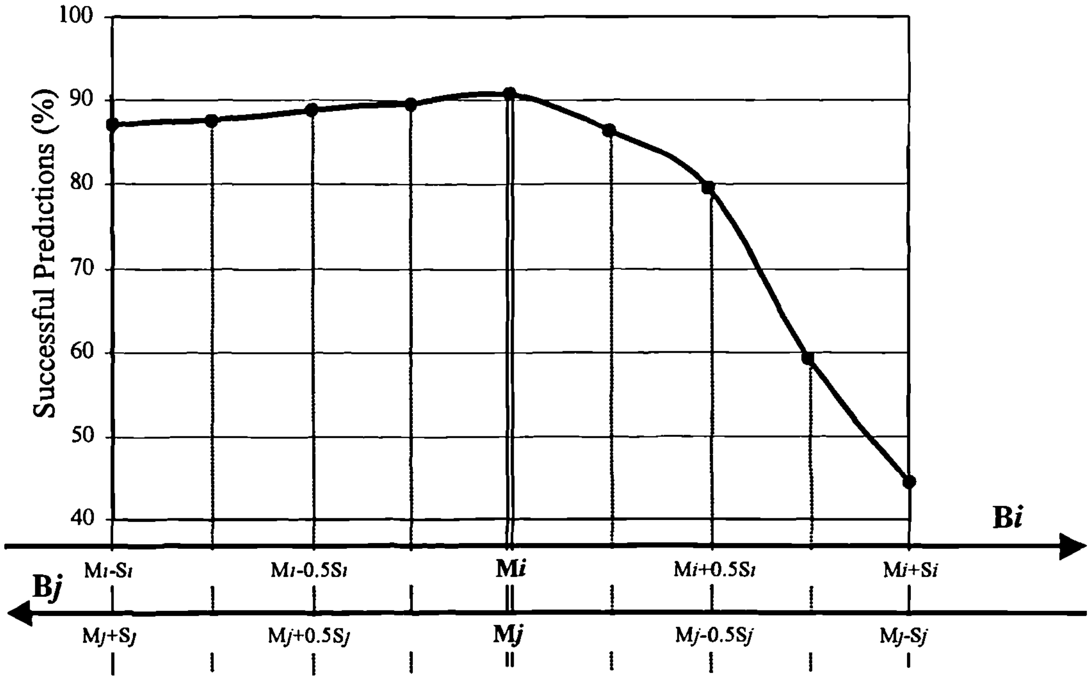



Fig. 5.10: The best values of B$i$ and B$j$

Where:

- $M_i$ is the mean of the neutral scores chosen by Syrian contractors for an encouraging factors ($F_i$);
- $S_i$ is the standard deviation of the neutral scores chosen by Syrian contractors for an encouraging factors ($F_i$);
- $M_j$ is the mean of the neutral scores chosen by Syrian contractors for a discouraging factors ($F_j$);
- $S_j$ is the standard deviation of the neutral scores chosen by Syrian contractors for a discouraging factors ($F_j$);
- The highest accuracy in predicting the actual decisions corresponds to $B_i = M_i$; and,
- $B_j = M_j$. Therefore, the "mean" was adopted for $B_i$ and $B_j$ in the final equation of the bidding index (BI).

Up to now, the assumed cut-off point between "bid" and "no bid" recommendations is (BI = 0). This might not be the optimum value.

Fig. 5.11 illustrates how the optimum value (X) is selected. One hundred and sixty two real bidding situations were used to select the optimum value of this point. Values around zero were tried. For each value, the number of the unsuccessful simulations was computed as presented in Table 5.6.

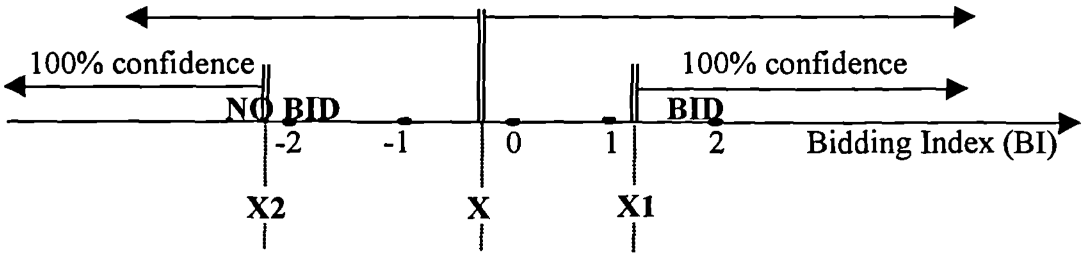



Figure 5.11: Selection of the optimum cut-off point between "Bid" and "No Bid"

Table 5.6: Selection of the best cut-off point between "bid" and "no bid"

| X | -2 | -1.5 | -1 | -0.5 | **0** | +0.5 | +1 | +1.5 | +2 |
|---|---|---|---|---|---|---|---|---|---|
| No. of unsuccessful recommendations | 21 | 20 | 20 | 16 | **15** | 17 | 19 | 22 | 24 |

The minimum number of unsuccessful predictions corresponds to X=0. Thus, the initial assumed cut-off point between "bid" and "no bid" recommendations stays unchanged (BI = 0).

### 5.3.3.3 Degree of Confidence:

The parametric model will recommend to bid on a new project ($P_k$) if the bidding index of this project was equal to/more than zero, i.e. $BI_k \geq 0$, and not to bid if $BI_k < 0$. To improve the quality of these recommendations, the model should be able to tell the user with what strength it recommends to bid or not to bid. To complement this bid/no bid model with such capacity, two cut-off points ($X_1$ and $X_2$ as illustrated in Fig. 5.12 are needed.

Where:

- If the bidding index (BI) of a certain project was equal or higher than $X_1$, the model will recommend to bid with a confidence CD = 1 (or 100%);
- If $0 < BI < X_1$, then "bid" with $CD = F_1(BI)$;
- If $X_2 < BI < 0$, then "no bid" with $CD = F_2(BI)$;
- If BI was less than $X_2$, the model will recommend not to bid with a confidence degree CD = 1.

One hundred and sixty two real bidding situations were used to select $X_1$ and $X_2$. The other twenty real projects were used in testing the final parametric model. The value of $X_1$ was set at a level, above which all contractors decided to bid ($X_1 = 5.162$). The value of $X_2$ was set at a level, below which all contractors decided not to bid ($X_2 = -7.811$).

Therefore, the parametric model will use the following procedure to calculate the strength of each bidding recommendation:

1- *If* $BI \geq (+5.162)$ *then* "Bid" with a confidence degree CDb= 1

2- *If* $0 < BI < (+5.162)$ *then* "Bid" with a confidence degree:

$$CDb = 0.5 * BI / 5.162 + 0.5$$

$$CDb = 0.097 * BI + 0.5 \tag{5.6}$$

3- *If* $BI = 0$ *then* "Bid" with a confidence degree $CD_k = 0.50$

4- *If* $0 > BI > (-7.811)$ *then* "No Bid" with a confidence degree:

$$CDnb = 0.5 * BI / -7.811 + 0.5$$

$$CDnb = -0.064 * BI + 0.5 \tag{5.7}$$

5- *If* $BI_k \leq (-7.811)$ *then* "No Bid" with a confidence degree CDnb =1.

6- $CDb = 1 - CDnb \quad (5.8)$

7- $CDnb = 1 - CDb \quad (5.9)$

Where:

CDb: is the confidence in a "bid" recommendation; and

CDnb: is the confidence in a "no bid" recommendation.

Fig. 5.12 illustrates how a confidence degree is produced for a recommendation.

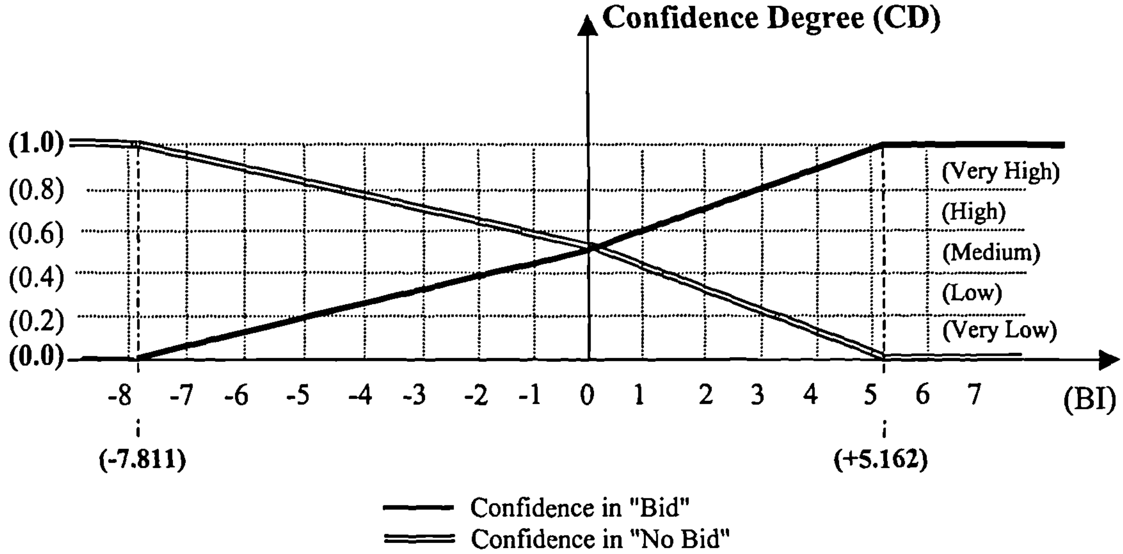



Fig. 5.12: Confidence degree based on the bidding index

This is a novel approach to determining the strength of the model's recommendation. It can be noticed from Fig. 5.10 that contractors tend to bid in situations, which are risky more than they stated in their response on the first questionnaire. This possibility explains why the validity of the model was improved when omitting the "risks expected" factor.

The confidence degree could be expressed as a percentage and it can be translated into linguistic expressions as illustrated in Table 5.7.

Table 5.7: Linguistic/percentage confidence degree.

| Confidence Degree | | | | | | |
|---|---|---|---|---|---|---|
| | **Linguistic** | Very low | Low | Medium | High | Very high |
| | **Percentage** | 0 - 0.20 | 0.20 - 0.40 | 0.40 - 0.60 | 0.60 - 0.80 | 0.80 - 1.00 |

#### 5.3.3.4 Testing and Validation

As mentioned earlier, twenty cases were selected randomly from the collected bidding situations and reserved for the validation process. The same cases were also used in testing the other "bid/no bid" models developed in the following two chapters for comparison proposes. The contractors' assessments of the bidding factors in each project of the testing cases were presented to the parametric "bid/no bid" model. Table 5.8 shows the actual decisions, the bidding indices, the model recommendations, and the degrees of confidence of the twenty testing cases.

Table 5.8: Twenty real-life bidding situations

| Project No. | Actual Decision | Bidding Index | Model Recommendation | Degree of confidence (%) | Degree of confidence Linguistic |
|---|---|---|---|---|---|
| 1 | Bid | 4.68 | Bid | 95.40 | Very High |
| 2 | Bid | 0.75 | No Bid | □ | □ |
| 3 | Bid | 4.66 | Bid | 95.40 | Very High |
| 4 | Bid | -0.75 | No Bid | 54.80 | Medium |
| 5 | Bid | 3.71 | Bid | 85.99 | Very High |
| 6 | Bid | 7.27 | Bid | 100 | Very High |
| 7 | Bid | 7.54 | Bid | 100 | Very High |
| 8 | No Bid | -6.53 | No Bid | 91.79 | Very High |
| 9 | No Bid | -9.78 | No Bid | 100 | Very high |
| 10 | No Bid | 3.66 | Bid | 85.72 | Very High |
| 11 | Bid | 9.06 | Bid | 100 | Very High |
| 12 | Bid | 9.72 | Bid | 100 | Very High |
| 13* | Bid | -3.34 | No Bid | 71.38 | High |
| 14 | Bid | 3.39 | Bid | 82.88 | Very High |
| 15 | No Bid | -6.66 | No Bid | 92.62 | Very High |
| 16 | No Bid | -3.55 | No Bid | 72.72 | High |
| 17 | No Bid | -10.19 | No Bid | 100 | Very High |
| 18 | Bid | 6.19 | Bid | 100 | Very High |
| 19 | Bid | 6.45 | Bid | 100 | Very High |
| 20 | No Bid | -6.86 | No Bid | 93.90 | Very High |

Although the bidding index of project 2 is positive, the model recommended not to bid because one bidding factor (fulfillment of the "to tender" conditions) violated its "kill" score (NB = 5). The actual contractor's assessment of this factor was CA = 4. The actual decision was "bid". The model failed to simulate the actual decisions of three other projects (4, 10, and 13). This implies that the proposed model is 80% accurate in simulating the actual bid/no bid decisions.

* In real life, the contractor's bid for project 13 was rejected by the client, which means that the model's recommendation (No Bid) is more appropriate. Taking this into account, it can be considered that the model produced the desired recommendations in 85% of the testing cases.

□ As the degree of confidence produced by this model is based on the bidding index, the model does not provide a confidence degree for project 2 where the final recommendations is based on one individual factor.

### 5.4 Mark up Development

After the development and validation of the "bid/no bid" part of the bidding model, the second part concerning the mark up selection needs to be developed. Multiple regression analysis techniques were used to develop a "mark up" model to help Syrian contractors in setting a competitive margin when bidding on new construction projects. The following sections explain the application linear and non-linear regression analysis on the mark up selection process.

#### 5.4.1 Selection of the Input Variables

Thirty eight mark up factors that are considered important by Syrian contractors were identified through a questionnaire survey (see section 4.5.1.6). These factors are listed in Table 4.5 in a descending order of importance in setting a competitive mark up. Twenty factors were selected as the most important as explained in section 4.5.1.9. Correlation analysis was performed on data collected on real-life bidding situations and eleven factors were selected as the most influential one, i.e. the most significantly correlated with the actual mark up values of the used sample (see section 4.5.2.3). These factors are considered as potential input variables for the mark up models developed in this study. The remaining factors were omitted because they have only marginal effect on the mark up size as suggested by their correlation coefficients (see Table 4.8).

#### 5.4.2 Mark up Selection: A Linear Regression Analysis Approach

The eleven factors selected in the previous section were used in an attempt to develop the linear regression equation that best fits the modelling sample (ninety six bidding situations).

The SPSS statistical package was used to perform various methods of linear regression (Enter, Stepwise, Forward, and Backward). The results of this analysis are summarised in Table 5.9.

Table 5.9: Comparison between different regression models

| | Linear | | | | Non-linear |
|---|---|---|---|---|---|
| | Enter | Stepwise | Forward | Backward | |
| Residual SS | 0.01633 | 0.0176 | 0.01701 | 0.01701 | 0.0108 |
| Adjusted R squared | 0.689 | 0.70384 | 0.713 | 0.713 | 0.81 |

The Forward and the Backward regression methods produced the same model, which considers only six input variables. The adjusted R squared of this model (0.713) is higher than that of the other linear models. Therefore, it was selected as the best-fit linear regression model although its sum of squared residuals (SS Residuals = 0.01710) is slightly higher than the SS Residuals of the model produced by the "Enter" method (0.01633), which considers all the eleven factors. Table 5.10 shows the T values of the mark up factors produced by the Forward regression method. Asterisks in the last column of same table denote the factors that are considered in this method.

Table 4.10: Selection of input variables for the linear regression model

| No. | The most influential mark-up factors | T | Signif T |
|---|---|---|---|
| 1 | Risks expected | 4.737 | 0.0000* |
| 2 | Availability of equipment owned by the contractor | -1.728 | 0.0874* |
| 3 | Confidence in the cost estimate | -2.080 | 0.0404* |
| 4 | Availability of materials required | -2.595 | 0.0111* |
| 5 | Competence of the expected competitors | -3.366 | 0.0011* |
| 6 | Degree of buildability | -1.367 | 0.1751 |
| 7 | Expected degree of competition (number of competitors) | -0.876 | 0.3834 |
| 8 | Way of construction (mechanically/ manually) | -2.114 | 0.0374* |
| 9 | Rigidity of specifications | 0.379 | 0.7057 |
| 10 | Site clearance of obstructions | -0.692 | 0.4906 |
| 11 | Site accessibility | -0.293 | 0.7701 |

* Denoting the considered factors in the linear regression model

The selected linear model is given in the following equation:

$$\text{Mark up} = 0.221841 - 0.006842*F_1 - 0.005385*F_2 - 0.00314*F_3 + 0.00677*F_4 - 0.002333*F_5 - 0.00816*F_8 \qquad (5.10)$$

The linearity assumed in this model might or might not be true. Thus, a non-linear regression approach was implemented to develop the best possible non-linear mark up model as explained in the next section.

### 5.4.3 Mark up Selection: A Non-Linear Regression Approach

The development of a non-linear regression model is basically an iterative trial and error process. Standard procedures are not available for developing non-linear regression models. In this work, an attempt was made to systemise this process as summarised below:

1. The actual mark ups of the modelling sample were plotted against the contractors' assessments of each individual factor using scatter diagrams.
2. The best trend line with its equation and the R squared value were produced for each factor (see figures 4.28 to 4.39).
3. The individual equations provided a range of non-linear parameters to choose from during the development of non-linear models. Starting with the equation of the "risks expected" factor (because it has the highest R square), parameters from the second equations (equipment owned) were added one parameter a time. Each time, the resultant equation was experimented with using the SPSS package and the produced R square was recorded. When adding a parameter reduced the R square value, this parameter was omitted.

In this way, more than seventy equations (see Appendix C) were examined before developing the final non-linear mark up model shown below:

$$
\begin{aligned}
\text{Mark up} = {} & -9.441112279-0.00628225*F_1+0.003808863*F_1^{\wedge}2- \\
& 0.000284558*F_1^{\wedge}3-0.288816319*F_2+0.06137285*F_2^{\wedge}2- \\
& 0.004294553*F_2^{\wedge}3-0.002802286*\mathrm{EXP}(0.419293361*F_3)- \\
& 0.165006062*F_4+0.03508057*F_4^{\wedge}2-0.002483252*F_4^{\wedge}3- \\
& 0.011653475*F_5+0.00396265*F_5^{\wedge}2-0.000437456*F_5^{\wedge}3+ \\
& 0.510946414*F_6-0.186452872*F_6^{\wedge}2+0.029107653*F_6^{\wedge}3- \\
& 0.001653161*F_6^{\wedge}4+12.377261191*F_7-6.887296762*F_7^{\wedge}2+ \\
& 1.846476669*F_7^{\wedge}3-0.23931915*F_7^{\wedge}4+0.012030553*F_7^{\wedge}5- \\
& 0.094035992*F_8+0.109280611*F_8^{\wedge}2-0.05144907*F_8^{\wedge}3+ \\
& 0.010500718*F_8^{\wedge}4-0.000774616*F_8^{\wedge}5+0.509122872*F_9- \\
& 0.199398855*F_9^{\wedge}2+0.032903452*F_9^{\wedge}3-0.001948869*F_9^{\wedge}4- \\
& 10.98309836*\mathrm{EXP}(0.000259526*F_{10})+17.130708662*F_{11}- \\
& 9.522532569*F_{11}^{\wedge}2+2.548534709*F_{11}^{\wedge}3-0.32951393*F_{11}^{\wedge}4+ \\
& 0.016513874*F_{11}^{\wedge}5 \qquad (5.11)
\end{aligned}
$$

The adjusted R-squared and the sum of squared residuals of this model are 0.81 and 0.0108 respectively as shown in the last column of Table 5.9. This provides evidence that the non-linear model fits the modelling data better than the linear model developed in the previous section. This will play a major role in deciding which regression model (linear or non-linear) should be selected.

### 5.4.4 Selection of the Final Regression Mark up Model

To decide whether the linear or the non-linear model should be chosen as the final regression mark up model, two criteria were considered:

- The determination coefficient (R squared) that indicates how well the model represents the modelling data; and,
- The model's ability to generalize solutions for new bidding situations, which have been used in the development process. The fifteen real-life bidding situations reserved for validation were used to test both the linear and the non-linear mark up models.

As found in the previous sections, the R square of the linear model is R= 0.713 while the R square of the non-linear one is R=0.81.

$R^2_{\text{Non-linear}} > R^2_{\text{Linear}}$. This is not enough to select the non-linear model. It is necessary to test both models against the bidding situations in the testing sample. The contractors assessments of these situations were presented to both regression models. The outputs of the regression models are shown in Table 5.11 with the actual values, the mean error (ME), and the roots mean square error (RMS). The linear and non-linear mark up recommendations are plotted against the actual values as shown in Fig. 5.13. The recommendations of the non-linear model are slightly closer to the actual mark ups compared to the linear model. Therefore, it was decided to select this model as the final regression mark up model. Some non-linear regression models are known of being unstable, i.e. small changes in the input space might cause large changes in the output space. Also, extreme inputs might cause producing unrealistic outputs. Therefore, the stability, i.e. robustness, of the non-linear model was examined as explained in the following section.

Table 5.11: Comparison between the linear and non-linear regression mark up models

| Project Number | Actual Mark up | Linear Model | | Non-linear Model | |
|---|---|---|---|---|---|
| | | Mark up | Error | Mark up | Error |
| 1 | 0.12 | 0.132 | -0.012 | 0.118 | 0.002 |
| 2 | 0.14 | 0.130 | 0.010 | 0.128 | 0.012 |
| 3 | 0.15 | 0.120 | 0.030 | 0.126 | 0.024 |
| 4 | 0.13 | 0.152 | -0.022 | 0.138 | -0.008 |
| 5 | 0.18 | 0.160 | 0.020 | 0.170 | 0.010 |
| 6 | 0.15 | 0.128 | 0.022 | 0.124 | 0.026 |
| 7 | 0.18 | 0.172 | 0.008 | 0.181 | -0.001 |
| 8 | 0.16 | 0.138 | 0.022 | 0.126 | 0.034 |
| 9 | 0.12 | 0.111 | 0.009 | 0.109 | 0.011 |
| 10 | 0.11 | 0.114 | -0.004 | 0.116 | -0.006 |
| 11 | 0.10 | 0.096 | 0.004 | 0.103 | -0.003 |
| 12 | 0.09 | 0.112 | -0.022 | 0.110 | -0.020 |
| 13 | 0.13 | 0.129 | 0.001 | 0.117 | 0.013 |
| 14 | 0.15 | 0.136 | 0.014 | 0.145 | 0.005 |
| 15 | 0.11 | 0.108 | 0.002 | 0.113 | -0.003 |
| ME | | 0.004 | | 0.005 | |
| RMS | | 0.0160 | | **0.0153** | |

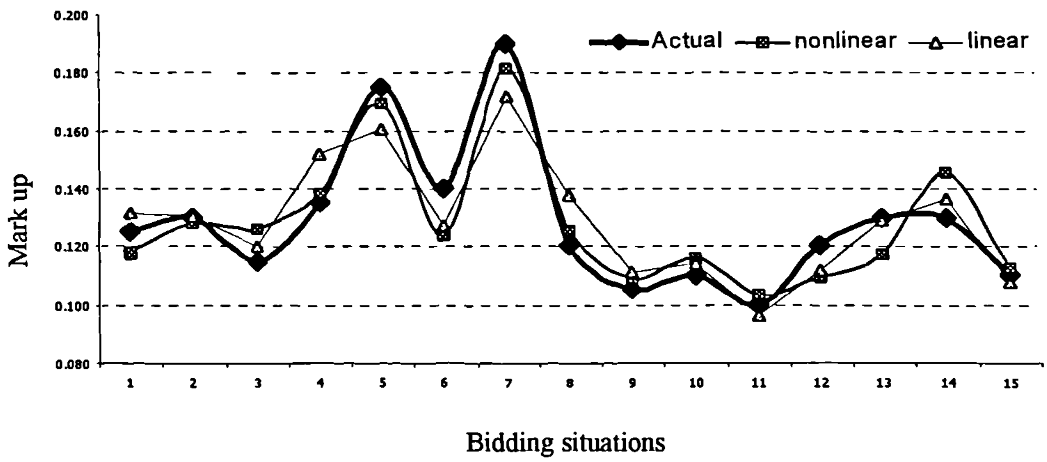



Fig. 5.13: Actual/predicted mark up size

### 5.4.5 Sensitivity Analysis

To test the robustness of the selected non-linear model, an analysis to examine the model sensitivity to variation in the inputs was carried out. The outputs of the model were recorded while changing the assessment selected for the first factor (F1). The other factors were set to the mid-point score (3).

The same process was repeated for all the factors. Table 5.12 shows the outputs produced by the model for different assessment given to its input variables.

Table 5.12: Sensitivity of the output of the non-linear model to variation in its inputs.

| Factors | Assessments | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | (3) | 4 | 5 | 6 |
| F1 | 0.1761 | 0.1734 | 0.1765 | 0.1839 | 0.1938 | 0.2044 | 0.2141 |
| F2 | 0.6139 | 0.3822 | 0.2475 | 0.1839 | 0.1658 | 0.1673 | 0.1628 |
| F3 | 0.1910 | 0.1895 | 0.1873 | 0.1839 | 0.1788 | 0.1710 | 0.1591 |
| F4 | 0.4302 | 0.2978 | 0.2207 | 0.1839 | 0.1726 | 0.1718 | 0.1667 |
| F5 | 0.1950 | 0.1869 | 0.1841 | 0.1839 | 0.1838 | 0.1811 | 0.1733 |
| F6 | -0.3229 | 0.0291 | 0.1596 | 0.1839 | 0.1774 | 0.1758 | 0.1753 |
| F7 | -8.3557 | -1.2465 | 0.1774 | 0.1839 | 0.1847 | 0.1788 | 0.1962 |
| F8 | 0.1921 | 0.1656 | 0.1727 | 0.1839 | 0.1666 | 0.1650 | 0.0345 |
| F9 | -0.2794 | 0.0613 | 0.1733 | 0.1839 | 0.1736 | 0.1761 | 0.1784 |
| F10 | 0.1925 | 0.1896 | 0.1868 | 0.1839 | 0.1810 | 0.1792 | 0.1753 |
| F11 | -11.638 | -1.7944 | 0.1777 | 0.1839 | 0.1851 | 0.1786 | 0.1803 |

Table 5.12 shows that the model will produce unusual recommendations, e.g. excessive mark up, if certain factors were assigned extreme scores. The modelling data dose not contain any case where similar extreme scores were assigned to the mark up factors. This might be the reason behind the model being unable to give reasonable recommendations in such cases. Additionally, it can be noticed from Table 5.12 that small variations in certain factors will cause big variation in the model output, which undermine the model's stability.

Similar analysis was performed for the linear regression model. The linear model proved to be more stable and it dose not produce similar unrealistic outputs. Therefore, integrating the two models was suggested as a solution for this problem. That is by using the linear model to recommend a mark up for situation where some factors are assigned extreme scores and using the non-linear in usual situation.

## 5.5 A Parametric and Regression Bidding Strategy Model

The parametric "bid/no bid" and the regression mark up models developed in the previous sections were combined to form an integrated bidding model to help contractors in dealing systematically with new bidding situations.

To use this practical bidding model, all a contractor needs is to provide his/her subjective assessment of the bidding situation under consideration in terms of nineteen predefined "bid/no bid" criteria. The estimate of the total cost expected and the available capital that can be devoted to the project are also required. Based on this information, the parametric bid/ no bid part of the model will recommend whether to bid or not. If the "No Bid" recommendation was made and accepted by the contractor, there is no need to proceed. The contractor can consider another project or even perform a what-if analysis for the same project.

On the other hand, if the final decision was to bid, the contractor can proceed by entering his/her assessment of the considered bidding situation in terms of the remaining mark up criteria in addition to the approximate cost provided by the client if available. The second part of the model, the regression mark up model, is activated then and a mark up percentage is recommended. The contractor can modify this percentage to produce the final bid price. Fig. 5.14 shows a flow chart of this integrated bidding model.

## 5.6 Discussion

The parametric process that was introduced in this chapter as a new tool for decision making proved a reasonable reliability in modelling the "bid/no bid" decision-making process. However, it has some limitations. For example, the effect of the "project size" on the "bid/no bid" decision was not explained clearly by the parametric process. Another two parameters are required to quantify the effect of this factor more accurately. It was assumed that there is one neutral score (B) above which the "project size" factor will have negative influence on the "bid" decision and above a kill-score (NB) will cause a "no bid" decision. This means that the smaller the project the more encouraging to bid on. In real life, big companies/ contractors usually are not interested in bidding on very small projects. To explain this phenomena more realistically, another neutral score ($B_1$) and another kill-score ($NB_1$) are required as shown in Fig. 5.15.

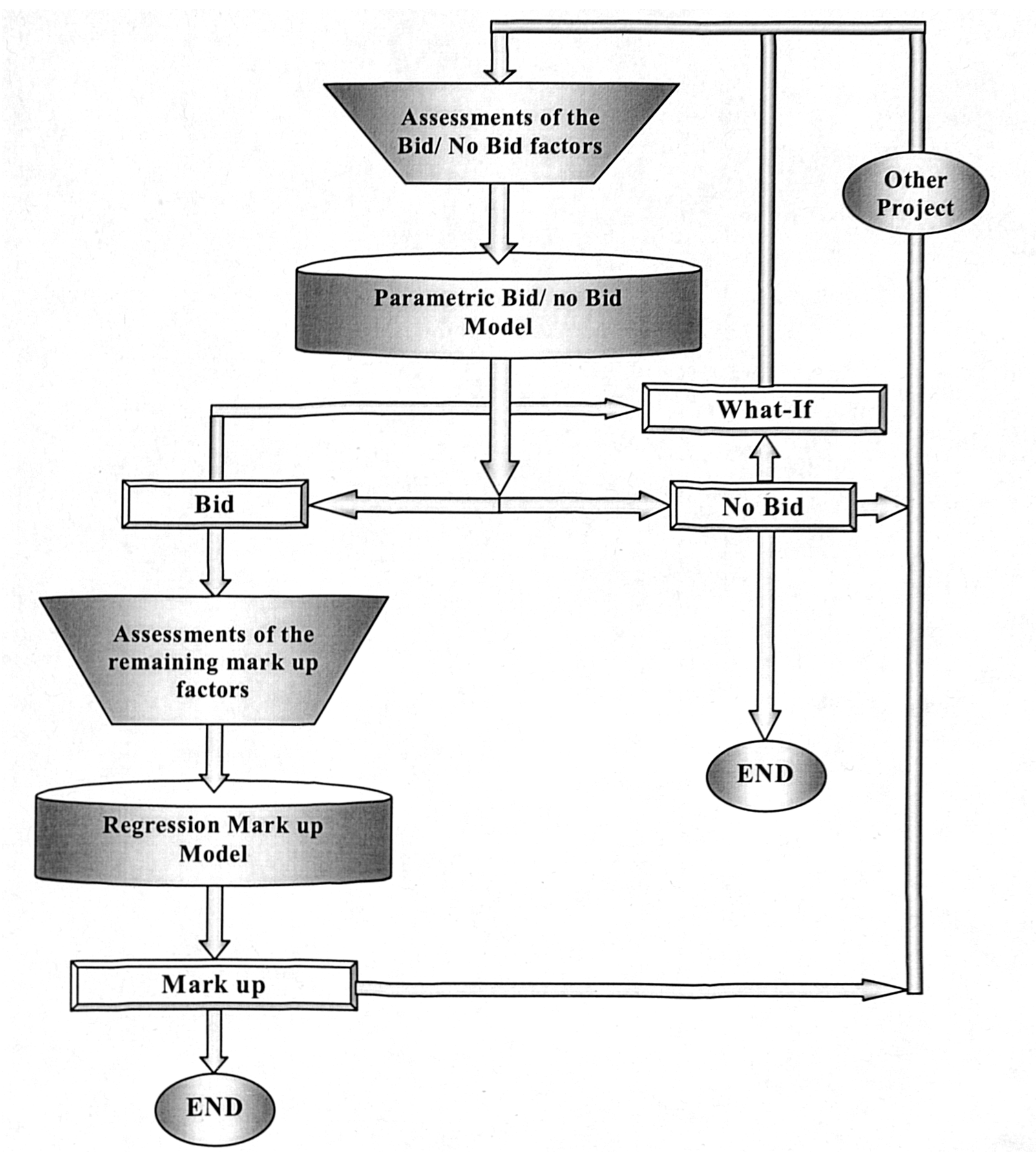



Fig. 5.15: An integrated parametric and regression bidding strategy model

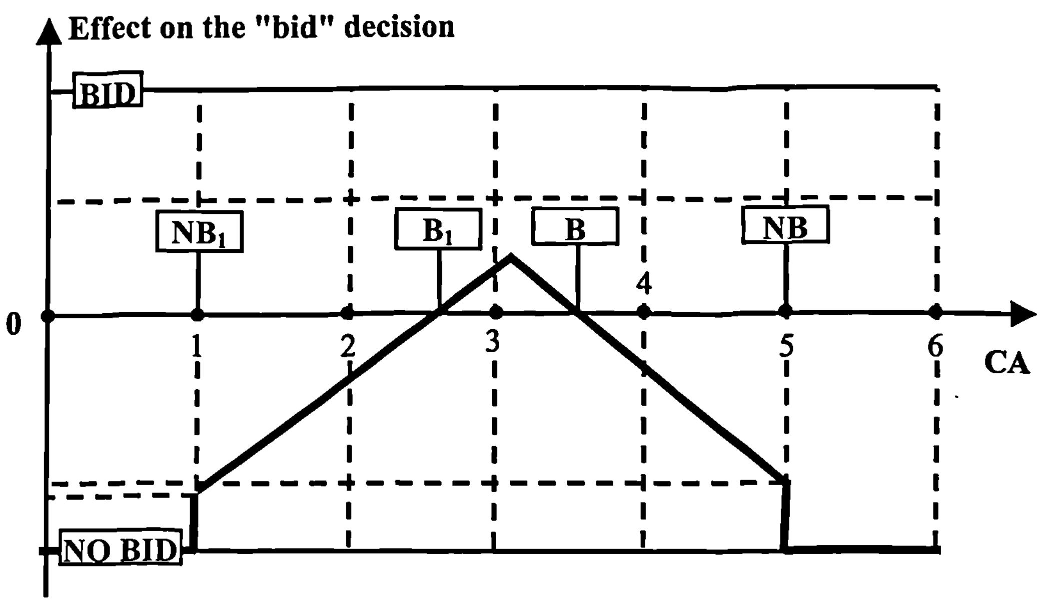



Fig 5.15: Effect of " project size" factor on the "bid" decision

Where:

- $B_l$ is a limit below which the project size will have negative effect on the "bid" decision.
- $NB_l$ is a limit below which the project size will cause a "no bid" recommendation.

Also, the parametric process assumes a linear influence of the decision's criteria on the final decision. This might or might not be the case. Thus, other techniques might be more effective in modelling this decision. The regression technique was tried. The result was not promising at all. Therefore, the ANN technique was used successfully and a neural network "bid/no bid" model was developed as explained in the next chapter. On the other hand, the main drawback of he mark up model developed in this chapter is being unstable, i.e. small variations in the inputs could cause big variations in the outputs. Also, extreme scores assigned to certain factors could result in producing unrealistic outputs. This implies that a more reliable mark up model is required. Moreover, to use the regression technique, it was assumed that the mark up factors are independent, i.e. there is not significant correlation between them. This assumption might or might not be realistic. To examine the rationality of this assumption, a detailed analysis has to be carried out and different non-linear regression models with different factors have to developed and tested. This task is very time-consuming and could result in developing another unstable model. Therefore, the neural network might be more suitable for modelling the process of making the bidding decisions. This will be investigated in the next chapter.

## 5.7 Summary

A simple systematic solution for one of the most critical problems faced by construction companies/contractors is presented. This bidding model is based on the findings of a formal questionnaire survey supported by semi-structured interviews, optimised using data on one hundred and sixty two real-life bidding situations, and validated against other twenty situations. The model proved to be 85% accurate in simulating the actual "bid/no bid" decisions. Some bidding experience that was provided by expert Syrian contractors is embedded in this model which could be very beneficial to contractors, who do not have such experience. This is not offered by any other bidding models. To improve the quality of the model output, a simple confidence model was imbedded in it to assess the strength of the bid/no bid recommendations. If the "Bid" decision was selected, the model is also able to help in setting a competitive mark up percentage based on the contractor's assessments of bidding situation under consideration. The proposed bidding model does not require as many inputs as the model developed by Ahmad (1988, 1990). All is required is some information about the bidding situation and subjectively assessing this situation in terms of predefined criteria. However, this model has some drawbacks such as:

1. Too many factors are considered when making "bid/no bid" recommendations;
2. The regression mark up equation selected might not be the best one. There might be a better equation with fewer factors being considered; and,
3. The regression models lack the ability to generalise solutions and adequately respond to highly correlated, incomplete, or previously unknown data. For such cases, the artificial neural networks technology (ANN) is superior to regression models (Boussabaine *et al,* 1999).

Thus, the ANN is suggested as an alternative tool for modelling the bidding process. The following chapter explains how the ANN is used to develop a neural network models for both "bid/no bid" and mark up decisions. Although the ANN does not guarantee that the best model will be found, it makes the search for the best model easier because it can find the equation automatically when presented with examples. Whereas, the non-linear regression analysis techniques require the user to provide the equations. All it does is to test the provided equations and show how well they represent the available samples.

# CHAPTER 6
# NEURAL NETWORK BIDDING MODEL

## 6.1 Introduction

The previous chapter explained the development process of the parametric and regression bidding model. The major limitations of this model were highlighted in section 5.7 raising a need to investigate the possibility of developing a more reliable bidding model. The nature of the bidding problem is highly unstructured and its outputs ("bid", "no bid" and "mark up size") are liable to be affected by numerous factors. It has been suggested by Moselhi et al (1991) and Boussabaine (1996) that the ANN technique is a useful tool in dealing with such problems. ANNs of the multi-layered type are essentially semi-parametric regression estimators. They can approximate virtually any measurable function up to an arbitrary accuracy (Hornik et al, 1989; Anders and Korn, 1999). Hence, it was decided to investigate the use of ANN in the bidding process. The main objectives of the current chapter are:

1. Investigating the applicability of the ANN technique on the "bid/no bid" decision-making process; and,
2. Investigating the possibility of developing a neural network mark up model that is more reliable and accurate than the regression model developed in the previous chapter.

An ANN development software called "NeuralWorks Professional II/ Plus" was used in the development process. Data on one hundred and eighty two real-life projects were preprocessed and transformed into series of inputs output patterns. Some cases were randomly selected and used in testing the developed models. The other examples were used in training numerous neural network configurations. The final "bid/no bid" and "mark up selection" models were integrated to develop an ANN bidding strategy model to help contractors in making their bidding decisions. This strategy model was implemented in a user-friendly spreadsheet prototype called "Smart Bidder", which dose not require any ANN knowledge. The major limitations of the developed ANN bidding model are highlighted and possible improvement using the neurofuzzy technology was pointed out in the last section.

## 6.2 Why ANN?

Potential applications of the ANN to various construction decisions have been highlighted by Moselhi *et al* (1991), Flood and Kartam (1994b), Boussabaine (1996) and Anderson and Gaarlev (1996) (see section 2.6.2.1). The literature contains many attempts to model the "mark up selection" process using ANN with reasonable degrees of success (Moselhi et al, 1991; Li, 1996a and others) (see section 3.2.2.3). Those researchers have claimed that the ANN technique is suitable for modelling the mark up process because it is highly unstructured process.

Also, the "bid/no bid" decision making is an unstructured process and it is characterised by several factors the influence of which is difficult to quantify individually and in combination leading it self to be a potential application of the ANN technique. Therefore, it has been decided to apply this technique not only to the second part of the bidding process (mark up selection) as other researchers did but, also, to investigate the applicability of this technique to the first part (bid/no bid). The major justification for the use of ANN as a tool to help in making the bidding decisions is its approximation ability to learn the underlying functional relationships from real bidding situations, which can be collected easily from contractors. Also, ANN techniques can produce meaningful solutions to problems even when input data contains errors or is incomplete, can adopt solutions over time to compensate for changing circumstances, process information rapidly, and transfer rapidly between computing systems (Bousabaine, 1995a). The next section explains the general methodology adopted in this chapter to develop a neural network model for the bidding process. Basic concepts of neural networks are provided in section 2.6.2.

## 6.3 Methodology

Fig. 6.1 illustrates the general methodology used to develop the neural networks bidding models for making both the "bid/no bid" and "mark up selection" decisions. The factors that are considered by Syrian contractors when making their bidding decisions were identified through formal questionnaire survey supported by semi-structured interviews. Unimportant factors were omitted and the remaining twenty-six factors were considered in preparing other questionnaire to collect data on real bidding situations (see section 4.14). Data on one hundred and eighty two projects were provided by contractors. These data were preprocessed and transformed into series of inputs output patterns. Sample of independent cases were randomly selected and used only in testing and validating the developed models. The remaining cases were used for training.

Using the NeuralWorks development package, an initial network configuration is designed and presented with the training examples for a fixed number of iterations (50000) and the training results in terms of predefined criteria (the root mean square error RMS and the correlation coefficient $R^2$) are recorded. The trained model is, then, tested using the independent cases that were not used in the training process. The test results, in terms of RMS and $R^2$, are recorded. If the performance of the experimented model in training and testing phases is not acceptable, its configuration is modified, trained, and tested again. This process is repeated as many times as possible in a guided trail and error process as explained in section 6.4.1.6. Then, the best model is selected. The selection of the best model is based on the best combination of the following criteria:

1. High training performance, i.e. small $RMS_{Training}$ and high $R^2_{Training}$;
2. High generalisation ability when applied to unseen data, small $RMS_{Testing}$ and high $R^2_{Testing}$; and,
3. Few input variables.

After selecting the best model, a validation process is carried out using independent real-life bidding situations.

The following sections explain in more details the modelling process of the neural network " bid/no bid" and "mark up selection" models.

### 6.4 Development of the ANN "Bid/No Bid" Model

The development of the "bid/no bid" decision-making process requires an in-depth study of this important activity. The factors that are perceived to have an influence on making such decision need to be identified and their influence should be quantified. The following sub-sections explain the systematic procedure used to develop an innovative "bid/no bid" model using the ANN technique, which has not been applied before to this process.

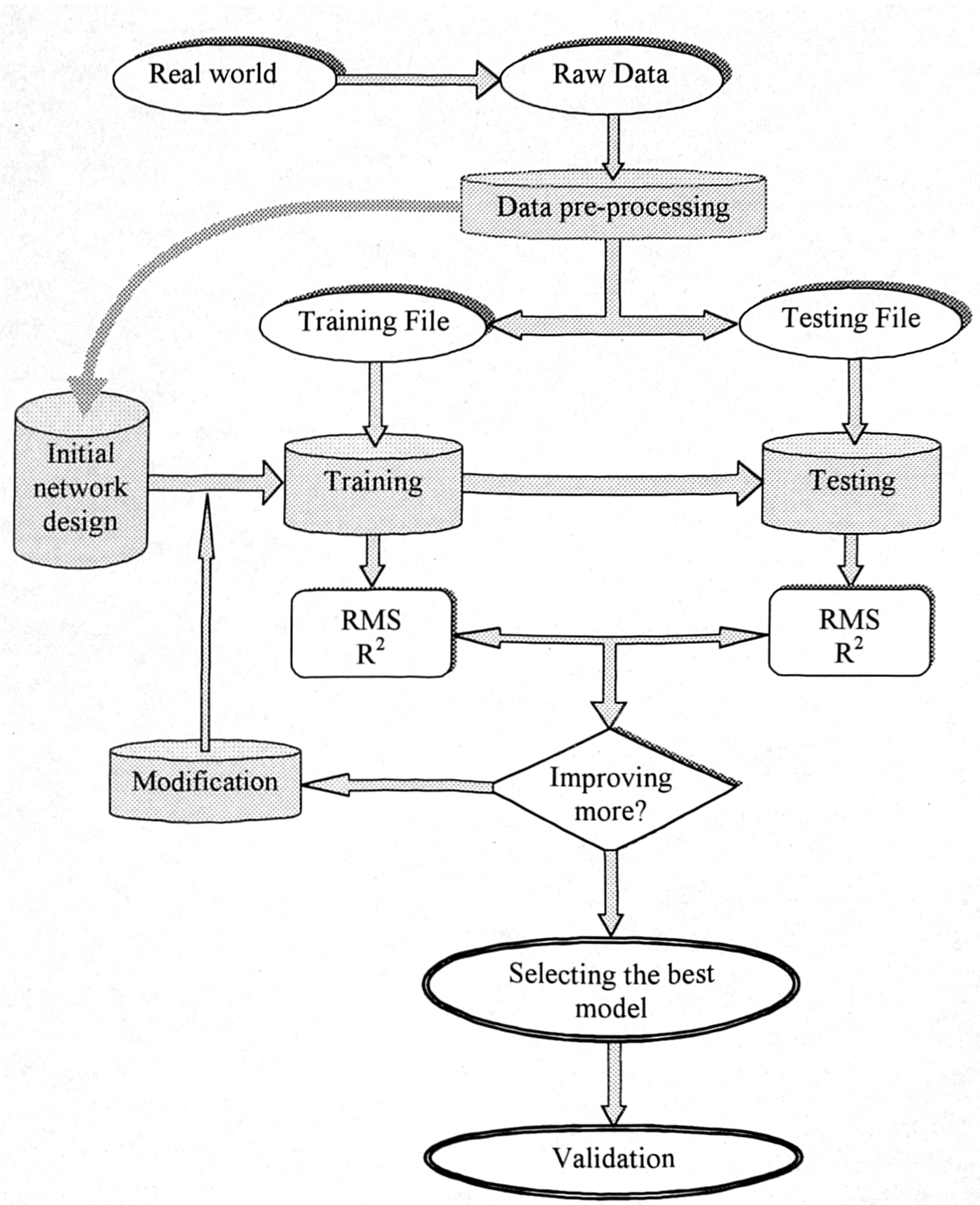



Fig. 6.1: General methodology of developing ANN models

### 6.4.1 The Modelling Process

One of the most unresolved questions in the literature on neural networks is what architecture should be used for a given problem (Anders and Korn, 1999). In order to specify an architecture for a neural network model, it is essential to choose the most relevant input variables and the appropriate number properties of hidden unites. This section explains a structured framework for developing ANN models. The design of this framework is based on earlier efforts on developing practical strategies for developing ANN models (Boussabaine 1996, Hegazy, *et al* 1994 and Bailey & Thompson 1990). It consists of six phases as shown in Fig. 6.2. These phases are data preprocessing, initial design, training, testing, modification, and selection of the best model process. The following sections explain the development phases in more details.

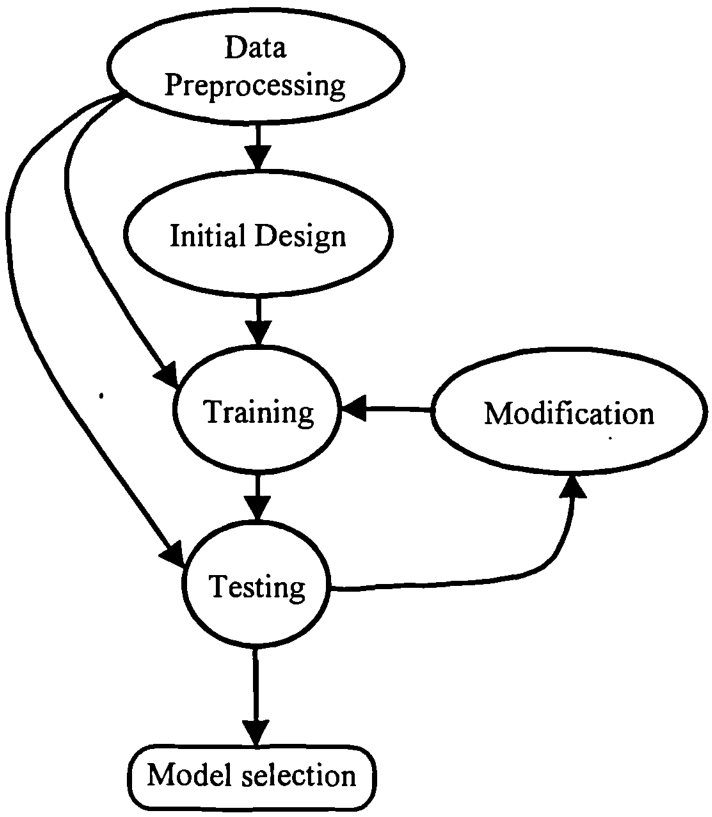



Fig. 6.2: Framework for developing ANN models

#### 6.4.1.1 Data Preprocessing

The required data need to be collected, preprocessed, and transformed into pairs of inputs and outputs. As explained in chapter 4, data on the bidding practice was collected from the Syrian construction industry. Preprocessing this data involved the following tasks:

1. Discovery of errors in the data. Errors in data usually can be classified into the different categories (ambiguous, incorrect, random, systematic, wrong measurement, and missing values). The main errors in the collected data were of the "missing values" type. The missing values of a certain variable were replaced by the average value of this variable or by neutral values recommended by expert contractors. Preprocessing missing values in certain situations may be achieved by other ways such as linear interpolation.
2. Data analysis for the identification of variables that influence the "bid/no bid" decision-making process. This analysis revealed that thirty five factors are considered by Syrian contractors when making their "bid/no bid" decisions. However, it is not expected that all these factors should to be considered in modelling this process. Omitting some factors might not affect or even improve the model performance. These unimportant factors should be omitted.
3. Data analysis for selecting the variables that need to be considered in the modelling process. This is the most important part of the data preprocessing stage. Therefore, it is explained in details in the next sub-section.
4. Transformation of the data set into the form that is acceptable by the used development software, "NeuralWorks Professional II/ Plus". The data were organised as a set of pairs of inputs, i.e. subjective assessments of the considered factors, and the corresponding output, i.e. "bid" or " no bid". Each input variable is a score on continuos scale from 0 to 6 where 0 is extremely low and 6 is extremely high. The output values are 0 for "no bid" and 1 for "bid". The general format required by the NeuralWorks software for the input output (IO) files is explained in Appendix D.
5. Dividing the available data into two sets; training and testing cases (see appendix E). Twenty bidding situations were selected randomly for the validation process. The remaining one hundred and sixty two cases were used in training. Training and testing cases are kept in separated Excel/tab delimited files. Fig. 6.3 shows the general form of the training/testing files.

Input Factors
Scores between 0 and 6

Output
0 for "no bid" and 1 for "bid"

| !@ $F_1$ | $F_2$ | | $F_i$ | | $F_n$ | BidNoBid |
|---|---|---|---|---|---|---|
| | | | S1 | | | 0 or 1 |
| | | | S2 | | | 0 or 1 |
| | | | | | | |
| | | | | | | |
| | | | Sn | | | 0 or 1 |

Fig. 6.3: Format of the training/testing files

#### 6.4.1.1.1 Selection of the Input Variables

In developing any mathematical model, it is generally accepted that it should be kept as simple as possible. This includes reducing the number of input variables to as few as possible without compromising the model performance considerably. In other word, the optimal ANN model is the model that has the best variance explained with few input variables. Thus, it is essential to identify the most influential variables that characterise the "bid/no bid" process before trying to develop an ANN model for it. This can be based on statistics and judgement or on trying different combinations of all the identified variables and developing ANN model for each combination and then testing all the developed models to select the best one. In this study, the following approach is adopted to select what variables that should be considered as inputs of the final ANN "bid/no bid" model without going through an endless trail and error process:

Step 1:

Considering variables that have importance index higher than a certain threshold. The same twenty two variables that were first selected for developing the parametric model (see Fig. 4.12) are considered in this stage. But, due to the constraints of the software used and to compare the reliability of the ANN and the parametric process technique considering the same factors, only the nineteen factors that are included in the final optimised parametric model are considered in this step. An asterisk in column five of Table 6.2 indicates these factors (S1).

Step 2:

Simple correlation analysis was carried out on the training data set. Table 6.1 shows the result of this analysis. The relative influences of the nineteen factors selected in Step 1 on the "bid/no bid" decision were evaluated by ranking the correlation coefficients of these factors as shown in Table 6.2.

The factors whose absolute correlation coefficients are equal to/ higher than 0.4 are considered in this stage. Twelve factors have 0.4 or greater absolute correlation with the output (bid/no bid) as illustrated in Fig. 4. 14. An asterisk in column six of Table 6.2 indicates these factors (S2).

Step 3:

The neural network technique is based on the assumption that the input variables are independent, i.e. they should not be significantly correlated to each other (Master, 1993). Taking this assumption into consideration, the dependent variables should be discarded. Thus, the interrelationship between the factors selected in Step 2 was examined using the training data as shown in Table 6.1. The correlation coefficients that are equal to or greater than (0.5) are highlighted. If the correlation between any two factors is equal to/greater than 0.5, one of these factors is discarded (the factor whose correlation with the output is smaller).

As a result, five of the twelve factors selected in Step 2 were omitted. The remaining seven factors (S3) are indicated by an asterisk in column seven of Table 6.2.

This selection procedure is summarised in Fig. 6.4, which shows how three sets of input variables are selected without going into an endless process of trying different combinations of all the bidding factors.

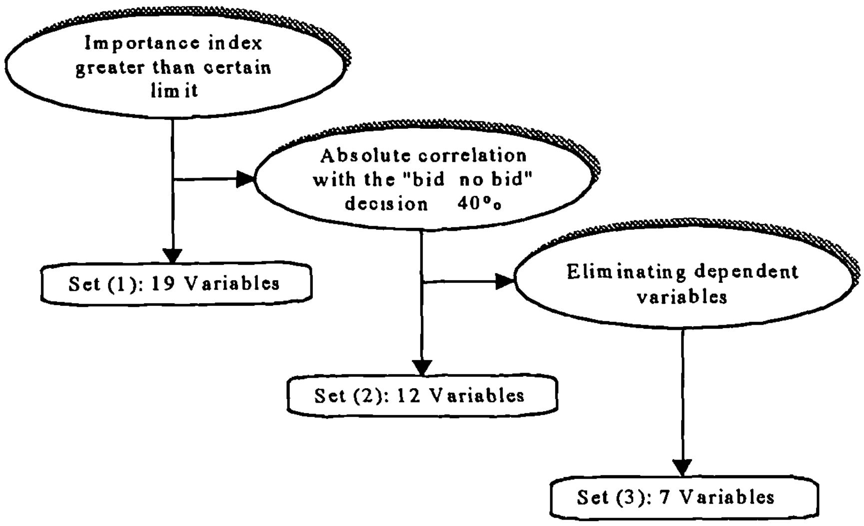



Fig. 6.4: Input factors to be considered in developing the ANN "bid/ no bid" model

Table 6.1: Correlation between the must influential bidding factors and the "bid/no bid" decision

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 | F10 | F11 | F12 | F13 | F14 | F15 | F1 | F17 | F18 | F19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| F1 | 1.00 | | | | | | | | | | | | | | | | | | |
| F2 | **0.54** | 1.00 | | | | | | | | | | | | | | | | | |
| F3 | 0.47 | **0.56** | 1.00 | | | | | | | | | | | | | | | | |
| F4 | -0.43 | -0.20 | -0.25 | 1.00 | | | | | | | | | | | | | | | |
| F5 | 0.40 | 0.39 | 0.35 | -0.33 | 1.00 | | | | | | | | | | | | | | |
| F6 | 0.44 | 0.36 | 0.29 | -0.38 | 0.26 | 1.00 | | | | | | | | | | | | | |
| F7 | 0.48 | 0.31 | 0.24 | -0.23 | 0.18 | 0.46 | 1.00 | | | | | | | | | | | | |
| F8 | **-0.54** | -0.31 | -0.20 | 0.37 | -0.29 | -0.40 | -0.31 | 1.00 | | | | | | | | | | | |
| F9 | 0.33 | 0.27 | 0.20 | -0.20 | 0.28 | 0.39 | 0.36 | -0.29 | 1.00 | | | | | | | | | | |
| F10 | -0.39 | -0.16 | -0.21 | 0.27 | -0.18 | -0.36 | -0.33 | 0.40 | -0.21 | 1.00 | | | | | | | | | |
| F11 | 0.41 | 0.20 | 0.09 | -0.22 | 0.18 | **0.53** | 0.43 | -0.34 | 0.29 | -0.31 | 1.00 | | | | | | | | |
| F12 | 0.12 | 0.07 | 0.12 | -0.15 | -0.01 | 0.42 | 0.29 | -0.18 | 0.15 | -0.25 | **0.52** | 1.00 | | | | | | | |
| F13 | 0.25 | 0.08 | 0.09 | -0.02 | 0.18 | 0.27 | 0.36 | -0.20 | **0.59** | -0.19 | 0.34 | 0.21 | 1.00 | | | | | | |
| F14 | 0.25 | 0.23 | 0.28 | -0.11 | 0.36 | 0.29 | 0.31 | -0.17 | 0.35 | -0.12 | 0.00 | 0.11 | 0.29 | 1.00 | | | | | |
| F15 | 0.39 | 0.28 | 0.29 | -0.18 | 0.21 | 0.39 | 0.45 | -0.27 | **0.55** | -0.32 | 0.27 | 0.24 | **0.54** | 0.43 | 1.00 | | | | |
| F16 | -0.35 | -0.33 | -0.23 | 0.24 | -0.20 | -0.27 | -0.13 | 0.37 | -0.10 | 0.20 | -0.13 | -0.03 | 0.00 | -0.26 | -0.18 | 1.00 | | | |
| F17 | -0.06 | 0.14 | 0.02 | 0.11 | 0.00 | -0.12 | -0.08 | -0.05 | -0.27 | 0.04 | -0.13 | -0.12 | -0.34 | -0.18 | -0.28 | -0.10 | 1.00 | | |
| F18 | 0.30 | 0.09 | 0.02 | -0.23 | 0.23 | 0.18 | 0.34 | -0.21 | **0.51** | -0.11 | 0.15 | 0.10 | 0.47 | 0.41 | **0.51** | -0.08 | -0.42 | 1.00 | |
| F19 | 0.44 | 0.47 | **0.54** | -0.21 | 0.34 | 0.29 | 0.16 | -0.18 | 0.18 | -0.07 | 0.06 | 0.05 | 0.04 | 0.35 | 0.26 | -0.33 | 0.04 | 0.12 | 1.00 |
| BnB | **0.69** | **0.44** | **0.41** | -0.36 | 0.38 | **0.52** | **0.57** | **-0.43** | **0.51** | **-0.42** | 0.34 | 0.16 | **0.46** | **0.49** | **0.64** | -0.33 | -0.30 | 0.38 | **0.41** |

BnB: The Bid/no bid decision

Table 6.2: Selection of potential input variables for the ANN "bid/no bid" model

| No. | Factor Name | r | \|r\| | S1 | S2 | S3 |
|---|---|---|---|---|---|---|
| F1 | Fulfilling the to-tender conditions | +0.691 | 0.691 | * | * | * |
| F2 | Site accessibility | +0.639 | 0.639 | * | * | * |
| F3 | Site clearance of obstructions | +0.570 | 0.570 | * | * | * |
| F4 | Availability of capital required | +0.518 | 0.518 | * | * | * |
| F5 | Availability of materials required | +0.512 | 0.512 | * | * | |
| F6 | Proportions that could be constructed mechanically | +0.492 | 0.492 | * | * | * |
| F7 | Confidence in the cost estimate | +0.456 | 0.456 | * | * | |
| F8 | Financial capability of the client | +0.444 | 0.444 | * | * | |
| F9 | Public objection | -0.432 | 0.432 | * | * | |
| F10 | Current workload | -0.419 | 0.419 | * | * | * |
| F11 | Relation with/ reputation of the client | +0.415 | 0.415 | * | * | * |
| F12 | Favourability of the cash flow | +0.408 | 0.408 | * | * | |
| F13 | Availability of time to tender | +0.376 | 0.376 | * | | |
| F14 | Project size | -0.360 | 0.360 | * | | |
| F15 | Experience on similar projects | +0.338 | 0.338 | * | | |
| F16 | Availability of skilled labour | +0.305 | 0.305 | * | | |
| F17 | Rigidity of specifications | -0.301 | 0.301 | * | | |
| F18 | Availability of equipment required | +0.163 | 0.163 | * | | |
| F19 | Sufficiency of the project duration | +0.150 | 0.150 | * | | |

The selection method considers the most important selection criteria, which are selecting the important factors that have high influence on the output, i.e. have significant relationship with the output, and are independent, i.e. not significantly correlated to each other. Considering each one of these input variables groups (S1, S2, and S3), several ANN models were experimented with in section 6.4.1.6. The model that has the best combination of high performance, high generalisation ability, and few inputs is selected as the best ANN "bid/no bid" model. The design of the initial model is explained in the following section.

### 6.4.1.2 Initial Design Decisions

The main decisions that need to be made in this phase are:

1. Number of inputs (based on data pre-processing);
2. Number of outputs;
3. Number of hidden layers;
4. Number of nodes, i.e. Processing Elements (PEs), in each hidden layer;
5. Type of Transfer Function (TF);

6. Type of Learning Rule (LR);
7. Connectivity; and,
8. Learning parameters, learning rate, epoch size, and momentum.

In this stage, the nineteen "bid/no bid" criteria included in the first set (S1) are considered as the model inputs. The continuous mode is adopted for these inputs as each one can take a value on a continuous scale from 0 (extremely low) to 6 (extremely high). The binary mode was not adopted whereas the number of the nodes in the input buffer will increase, without any transformation, from (19) to (19*7 = 133). This is because each input variable will be divided into 7 sub-inputs which accept either 0 or 1 as shown in Fig. 6.5.

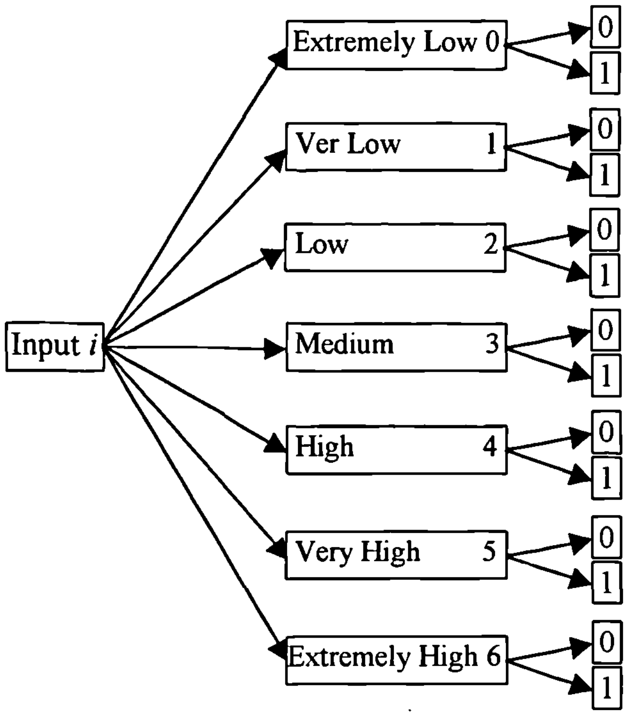



Fig. 6.5: Binary input mode

The binary model can be adopted for the output as is can be either "bid" or "no bid", i.e. 1 or 0 (yes or no). To produce such "1 or 0" output, the Threshold Logic Unit (TLU) transfer function can be used. This will suppress the uncertainty and ambiguity in the recommendation reached. Therefore, the continuous mode is, also, adopted for the output even it has only two potential values. This is to enable the model to produce its recommendation with a certain degree of confidence rather than a definite decision. The output variable is called the Neural Bidding Index (NBI).

Based on the NBI, a "bid/no bid" recommendation with a certain degree of confidence is produced using the confidence sub-model that transforms the NBI into the final output as explained in section 6.4.2.1.

After selecting the number and the mode of the input/output variables, the number of the hidden layers and their PEs, the TF, the LR, and model connectivity need to be determined. There are no hard rules for performing this task. However, the literature contains some rules of thumb concerning the development of ANN models. These include the following (Hegazy *et al*, 1994 and Boussabaine 1999):

1. Start with one hidden layer and add more if required;
2. With a single hidden layer, a suitable initial size is 75% of the size of the input buffer. For more than one hidden layer, reduce the size of each subsequent layer;
3. Binary input/output pairs can use TLU as a transfer function. Continuous-value input/output pairs use a form of sigmoid transfer function;
4. A network with a continuous-value inputs may required more than one hidden layer;
5. In continuous-value inputs and outputs, the number of PEs in the input buffer and the output layer is equal to the number of the input and output attributes respectively;
6. Generally, fully connected adjacent layers within multi-layer network are best; and,
7. The momentum can be set to (0.9).

With these rules in mind, the development process started by examining the simplest structure of the ANN "bid/no bid" model that considers the first group of inputs (S1). This structure is composed of the input buffer, which contains nineteen nodes fully connected to the output layer, which contains only one node. The sigmoid transfer function, and the "normalised cumulative delta" learning rule are uaed. The other parameters, i.e. learning coefficient, momentum, epoch size, are set to their default values selected in the software used (NeuralWorks Professional II Plus) as shown in Fig. D.1/ Appendix D. The "MinMax Table" and the "Bipolar Inputs" (see appendix D) options are selected. These options cause automatic linear scaling of real world data ranges into the "network target" ranges, within which the network performs better. As the sigmoid transfer function is used, network output target range is set to (0.20 , 0.80).

The input target range is set to (-1 , +1) as shown in Fig. D.2/ Appendix D. Having all the required design parameters selected for the initial ANN "bid/no bid" model (B. net1), the structure of this model is shown in Fig. 6.6. This structure is identical to a simple linear regression model as it has no hidden layers. B.net 1 will be trained and modified as explained in the subsequent sections. For detailed explanation of how a MinMax Table is generated and how does it work see Appendix D.

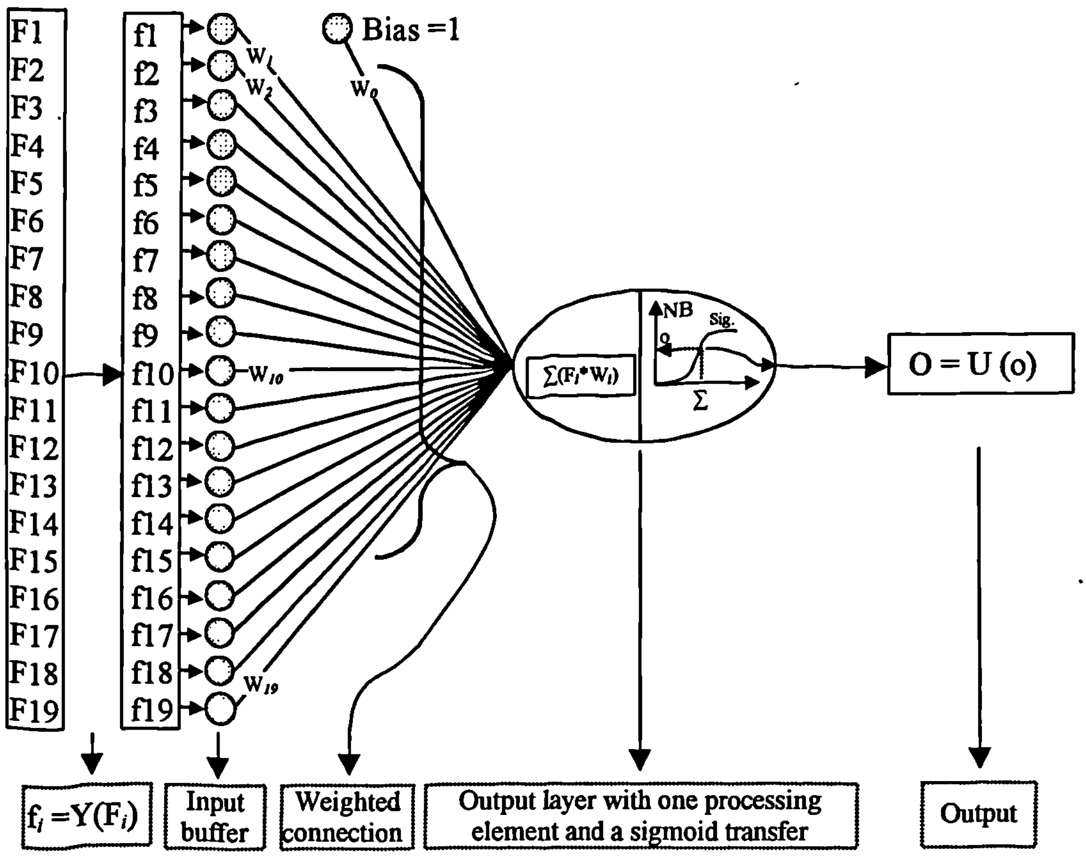



Fig. 6.6: Structure of the initial ANN "bid/no bid" model

#### 6.4.1.3 Training

This section explains how model B. net1 is trained. Before training, the real world training data are scaled automatically to fall between the desired input and output ranges, within which the network performs better.

In this stage, the network connection weights ($W_i$) are small random number between -0.5 and +0.5 set by the NeuralWorks automatically. The back propagation (BP) training algorithm is the most commonly used in ANN applications due to its high performance (Hegazy, 1994). Therefore, it was adopted in this study. The flow of the mathematical operations included in the training process is presented Appendix D. Two statistical measures of how close the predicted decisions to the actual ones are provided by the NeuralWorks software. These measures, i.e. diagnostic instruments, are $RMS_{train}$ (root mean square error) and $R^2_{train}$ (correlation coefficient). $RMS_{train}$ and $R^2_{train}$ of model (B. net1) are recorded in Table 6.3 after completing a fixed number of training iterations (50 000). The ability of the trained mode (B. net1) to explain the variance in the training data is presented by its $RMS_{train}$ and $R^2_{train}$ values. To examine the generalisation capability of this model, it should be tested using new bidding situations that have not been used in the training process. This is explained in the following section.

#### 6.4.1.4 Testing

In the "data pre-processing" phase, twenty bidding situations were selected randomly and stored in a separate file. Input and output values in this file were scaled using the same "MinMax Table" and the same network target ranges used for the training file. The scaled inputs of each record, i.e. cases, in the test file are presented to the trained model (B. net1), which produced an output for each record. The produced outputs were compared to the actual ones and two performance measures were provided by the NeuralWorks software as shown in Fig. 6.7. These measures ($RMS_{test}$ and $R^2_{test}$) are recorded in Table 6.3. Also, NeuralWorks de-scales the initial outputs automatically to the real world values as explained in section 6.4.1.2.1. The final de-scaled output was called the NBI. Initially, the bidding indices equal to or higher than (0.5) were translated into "bid" recommendations. Lower NBIs were translated into "no bid" recommendations. These "bid/no bid" recommendations were compared to the actual decisions of the test cases and the number of wrong recommendations is computed. The performance of the initial model B. net1 is assessed according to the following criteria:

- $RMS_{train}$ and $R^2_{train}$;
- $RMS_{test}$ and $R^2_{test}$; and,
- Percentage of wrong recommendations.

Values of these criteria were recorded for model B. net1 (and another models during the modification phase) in Table 6.4. Fig. 6.7 summarises the "training", and "testing" phases.

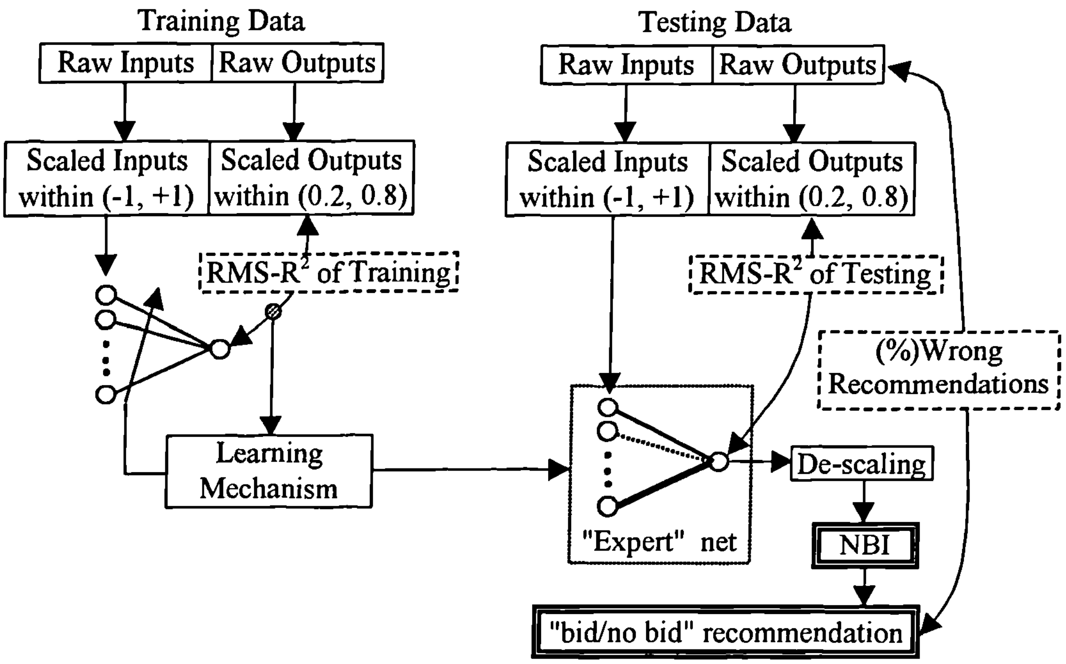



Fig. 6.7: A summary flowchart of training and testing

The following section explains a guided trial and error modification procedure adopted to get the best possible ANN "bid/no bid" model.

### 6.4.1.5 Modification

The performance of any ANN model depends on many factors, which include:

- Number of hidden layers;
- Number of PIs in the hidden layer;
- LR;
- TF;
- The momentum ($\eta$);
- Initial learning coefficient (Lcoef);
- The epoch size (E); and,
- Input factors considered.

The main aim of the modification phase is to identify the best combination of these modelling parameters. A systematic procedure was carried out to fine-tune these parameters to get the best combination of them, which corresponds to the best ANN "bid/no bid" model. The starting point is the initial model (B. net1), which was designed, trained, and tested. The modification procedure is explained as follows:

1. The initial model was modified by adding a hidden layer containing five processing elements. The resultant model (B.net2) was trained for a fixed number of iterations (50000) and, then, tested. The results of training and testing (RMS, and R) are recorded in Table 6.3. The percentage of wrong recommendations was computed and recorded in Table 6.4.
2. Step 1 was repeated by changing the number of processing elements (PEs) in the hidden layer to 10, 15, 20, 25, and 30 (B. net3 to B. net7). Each one of these models was trained the same (50000) iterations and, then, tested. The results of training and testing are also recorded in Table 6.3 and the percentages of wrong recommendations in Table 6.4. Fig. 6.8 shows the effect of number of PEs on learning and testing performance of models B. net1 to B. net 7. It can be seen that the best combination of high $R^2$s and low RMSs corresponds to twenty five PEs. However, one hidden layer might not be enough to learn the functional relationship between the "bid/no bid" variable and the final bidding decision. The need for additional hidden layer is investigated in the following steps.

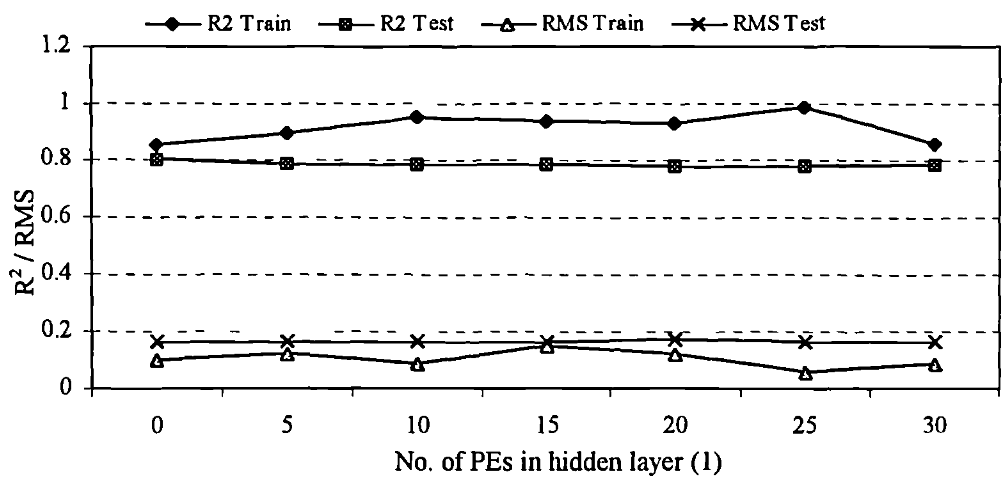



Fig. 6.8: Effect of Number of PEs in one hidden layer

3. After trying different number of processing elements in the first hidden layer, Another hidden layer was added. Different number of PIs (1, 2, 5, and 10) were examined in the second hidden layer with five PIs in the first one (B. nets 8 to 11). Fig. 6.9 shows that two PEs in the second hidden layer are more suitable when using five PEs in the fist one (5_2).

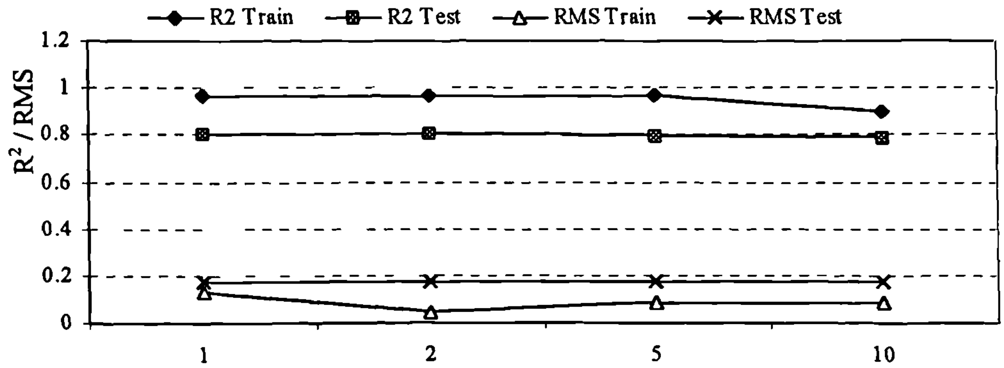



Fig. 6.9: Effect of Number of PEs in second hidden layer with 5 PEs in the first one

4. Different number of PIs (1, 2, 5, and 10) were examined in the second hidden layer with ten PIs in the first one (B. nets 12 to 15). Fig. 6.10 shows that two PEs in the second hidden layer are more suitable when using ten PEs in the first layer (10_2).

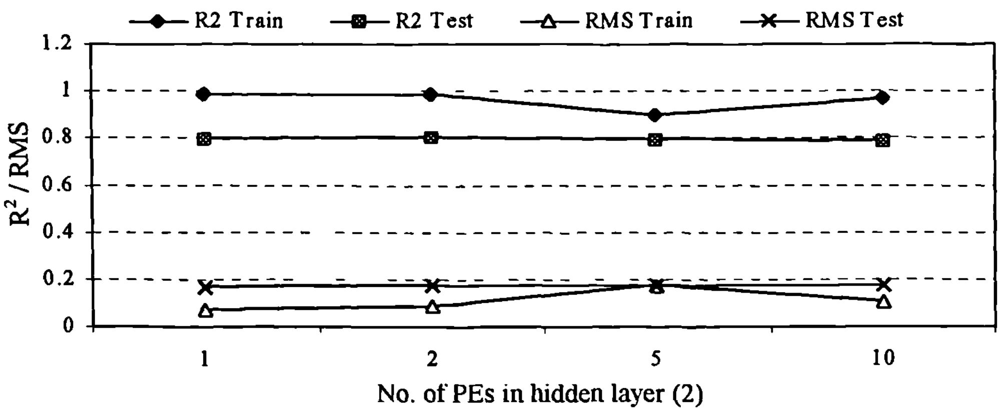



Fig. 6.10: Effect of Number of PEs in second hidden layer with 10 PEs in the first one

5. 1, 2, 5, and 10 PIs were examined in the second hidden layer with fifteen in the first one (B. nets 16 to 19). Fig. 6.11 shows that five PEs in the second hidden layer are more suitable when using fifteen PEs in the first layer (15_5).

6. The structures of hidden layers selected in the previous steps (0_0, 25_0, 5_2, 10_2, and 15_5) were compared with each other as shown in Fig. 6.12.

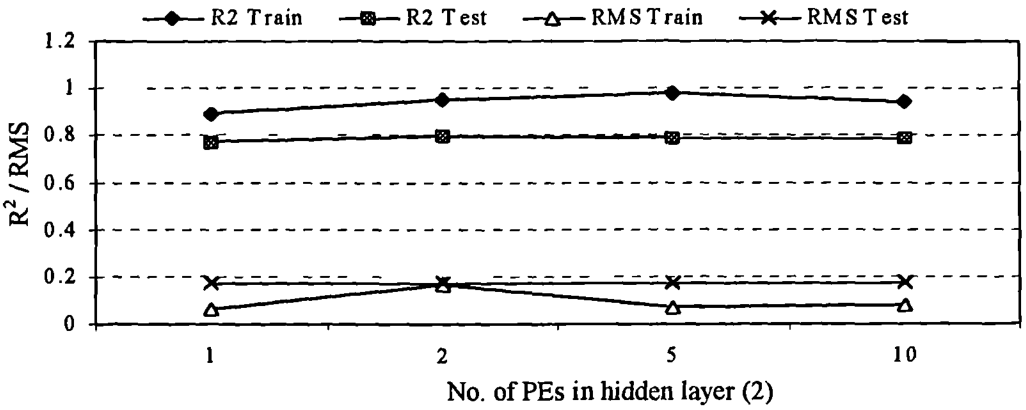



Fig. 6.11: Effect of Number of PEs in second hidden layer with 15 PEs in the first one

The structure of five PEs in the first hidden layer and two PEs in the second one was selected as the best structure and used in all the following models as indicated by being underlined.

7. Model (B. net10), which has two hidden layers with five PIs in the first layer and two PIs in the second one was experimented with different learning rules (B. nets 20 to 24). Fig. 6.13 shows that the normalised cumulative delta rule (N-C-D) is more suitable. Thus, it was used in all the following models as indicated by being underlined in Table 6.3.
8. Different transfer functions were tested (B. nets 25 to 28). The sigmoid transfer function is the most suitable one as shown in Fig. 6.14. Hence, it was used in all the subsequent models.

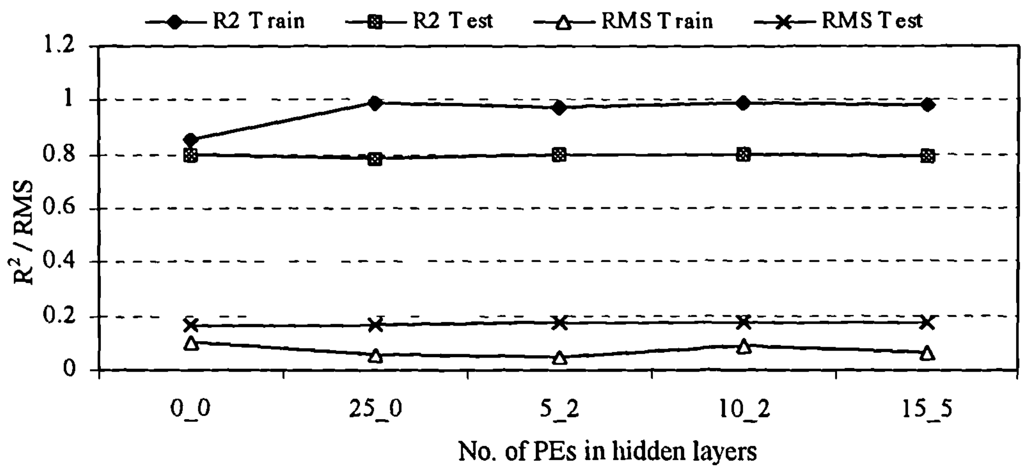



Fig. 6.12: Selection of the best structure of hidden PEs

9. Different epochs were examined (B. nets 29 to 34). Model B. net 29, which uses an epoch size of (E=5) showed some improvement over other models (see Fig. 6.15). Therefore, this epoch size was used in the subsequent models.

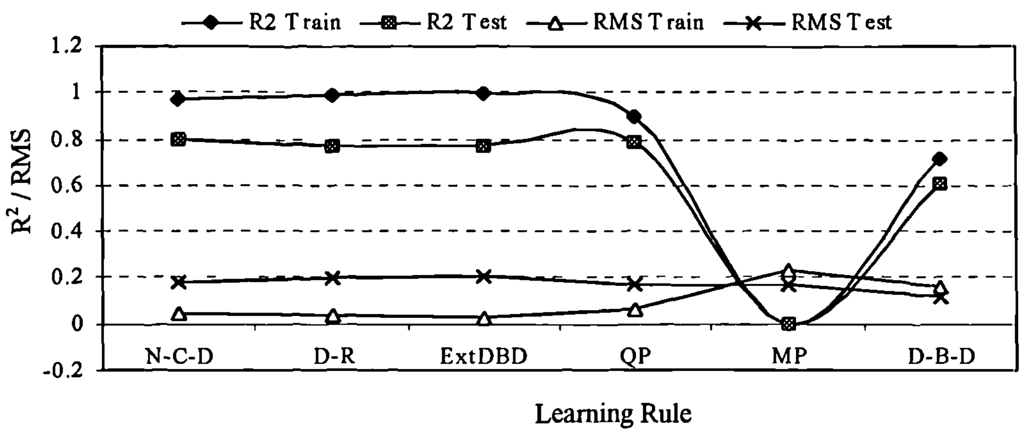



Fig. 6.13: Selection of the best learning rule

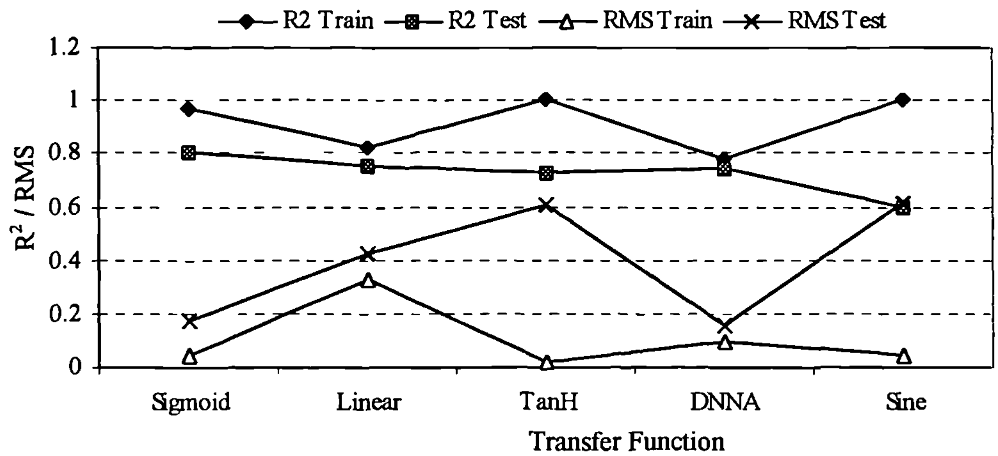



Fig. 6.14: Selection of the best transfer function

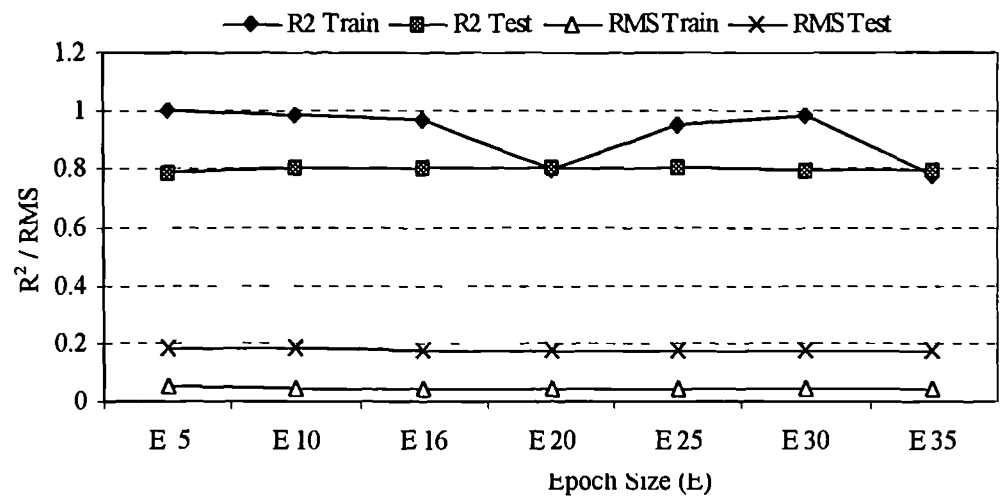



Fig. 6.15: Selection of the best epoch size

10. Different values were tested for the momentum parameter ($\eta$) (B. nets 35 to 39). ($\eta$=0.5) showed some improvement over the initial momentum ($\eta$=0.4) and over the value suggested by Hegazy *et al* (1994) ($\eta$=0.9) as shown in Fig. 6.16. Therefore, it was used for all subsequent models.

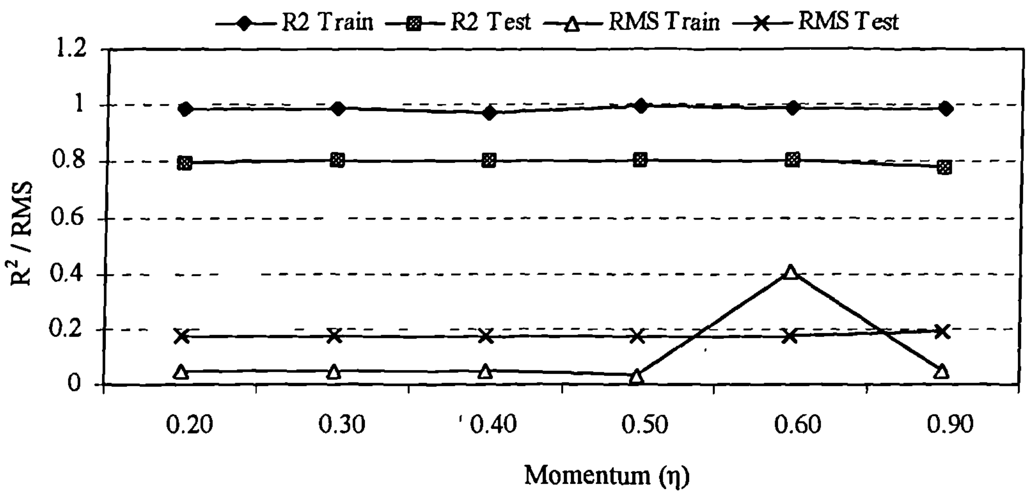



Fig. 6.16: Selection of the best Momentum

11. Different learning coefficients were examined for the first hidden layer (models B. nets 40 to 44). The default learning coefficient ($\alpha_1$ = 0.3) proved to be the best one as shown in Fig. 6.17. Also, different learning coefficients were tried in the second hidden layer ($\alpha_2$) and the output layer ($\alpha_o$) without any improvement over the default values ($\alpha_2$ = 0.2 and $\alpha_o$ = 0.15). Therefore, these values were fixed as the best learning coefficients and used in all the following models.

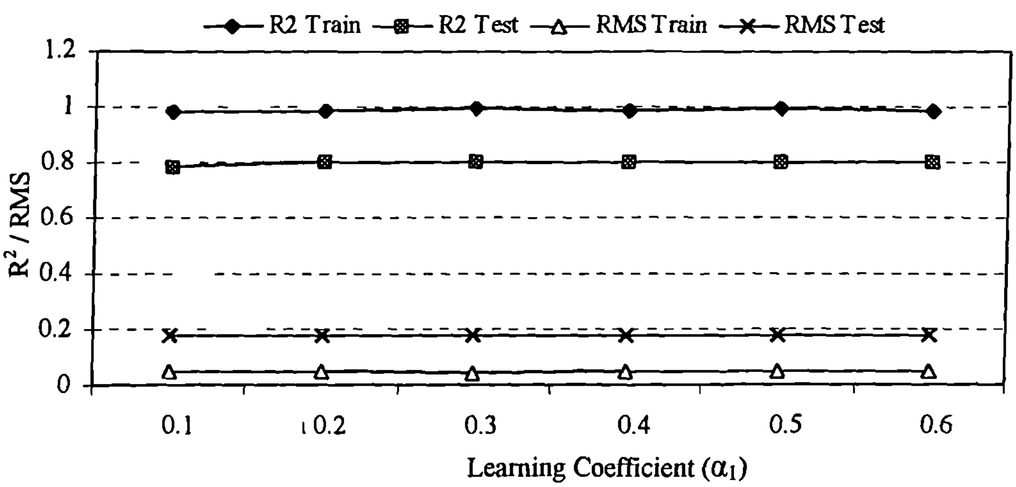



Fig. 6.17: Selection of the best learning coefficient

12. It can be concluded from the previous steps (models B. net1 to 44 in Table 6.3) that the best network structure that considers the nineteen input factors (S1 in Table 6.2) is as follows:
    - Two hidden layers with five PIs in the first layer and two PEs in the second one;
    - Epoch size (E=5);
    - Momentum ($\eta$=0.5); and,
    - Initial learning coefficients ($\alpha_1 = 0.3$, $\alpha_2 = 0.2$ and $\alpha_0 = 0.15$).

    This structure corresponds to model B. net 29. Thus, many experiments were made to improve the performance of this model by more training iterations (B. nets 45 to 47). Up to this point, the main modelling parameters were optimised including the number of hidden layers, number of PIs, learning rule, transfer function, epoch size, momentum, learning coefficient, and number of training iterations. There is still very important parameter needs to be optimised. This is the input variables' set.

    In section 6.4.1.1.1, three sets of bidding variables were proposed as the potential best inputs for the ANN "bid/no bid" model. The first input set (S1) was used in all the previous models (B. nets 1 to 47).
13. The same modelling parameters of model B. net 29 were adopted while considering the twelve bidding variables contained in S2 (see Table 6.2) as the input variables (model B. nets 48). This model was trained for extra iterations to get the best possible performance (B. nets 49 and 51).
14. As the number of inputs in S2 (12) is less than S1 (19), it was believed that the best model considering S2 variables might need less PEs in the hidden layers than the model considering S1 variables. Thus, the number of PEs was reduced to investigate this possibility (B. net 52). Further, model B. net 52 was trained for more iterations (B. net 53 to 55). These models show noticeable improvement over models B. net 48 to 51, which use the same inputs.
15. Only one hidden layer was used with 5, 4, 2 PEs in models B. nets 56 to 59. These models were trained for different iterations. Model B. net 60 was designed and trained without any hidden nodes.

Table 6.3: The modification process

| One output (NBI: Neural Bidding Index) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| B.Net | No. Inputs | No. of Hidden Layers | Nodes in H.L1 | Nodes in H.L2 | Iteration | L.R. | T.F. | Training | | Testing | |
| | | | | | | | | RMS | $R^2$ | RMS | $R^2$ |
| 1 | 19 S1 | 0 | 0 | 0 | 50000 | N-C-D E 16 η 0.40 α 0.30 | Seigmoid | 0.1022 | 0.8491 | 0.1658 | 0.7983 |
| 2 | | 1 | 5 | | | | | 0.1183 | 0.8938 | 0.1678 | 0.7856 |
| 3 | | | 10 | | | | | 0.0869 | 0.9469 | 0.1660 | 0.7823 |
| 4 | | | 15 | | | | | 0.1477 | 0.9365 | 0.1654 | 0.7844 |
| 5 | | | 20 | | | | | 0.1234 | 0.9308 | 0.1681 | 0.7797 |
| 6 | | | 25 | | | | | 0.0579 | 0.9836 | 0.1661 | 0.7820 |
| 7 | | | 30 | | | | | 0.0860 | 0.8574 | 0.1667 | 0.7824 |
| 8 | | 2 | 5 | 1 | | | | 0.1322 | 0.9710 | 0.1762 | 0.7989 |
| 9 | | | | 2 | | | | 0.0451 | 0.9668 | 0.1758 | 0.7991 |
| 10 | | | | 5 | | | | 0.0829 | 0.9706 | 0.1733 | 0.7925 |
| 11 | | | | 10 | | | | 0.0872 | 0.8959 | 0.1688 | 0.7890 |
| 12 | | 2 | 10 | 1 | | | | 0.0717 | 0.9818 | 0.1669 | 0.7960 |
| 13 | | | | 2 | | | | 0.0863 | 0.9880 | 0.1745 | 0.7991 |
| 14 | | | | 5 | | | | 0.1696 | 0.9012 | 0.1731 | 0.7906 |
| 15 | | | | 10 | | | | 0.1006 | 0.9689 | 0.1699 | 0.7876 |
| 16 | | 2 | 15 | 1 | | | | 0.0641 | 0.8860 | 0.1759 | 0.7649 |
| 17 | | | | 2 | | | | 0.1603 | 0.9464 | 0.1730 | 0.7912 |
| 18 | | | | 5 | | | | 0.0657 | 0.9761 | 0.1708 | 0.7891 |
| 19 | | | | 10 | | | | 0.0772 | 0.9424 | 0.1696 | 0.7836 |
| 20 | | 2 | 5 | 2 | 50000 | D-R | Seigmoid | 0.0301 | 0.9874 | 0.1985 | 0.7673 |
| 21 | | | | | | ExtDBD | | 0.0218 | 0.9926 | 0.1994 | 0.7693 |
| 22 | | | | | | QP | | 0.0620 | 0.8984 | 0.1706 | 0.7849 |
| 23 | | | | | | MP | | 0.2329 | -0.001 | 0.1703 | 0.0008 |
| 24 | | | | | | D-B-D | | 0.1559 | 0.7116 | 0.1175 | 0.6037 |
| 25 | | 2 | 5 | 2 | 50000 | N-C-D | Linear | 0.3284 | 0.8242 | 0.4241 | 0.7509 |
| 26 | | | | | | | TanH | 0.0175 | 0.9998 | 0.6022 | 0.7227 |
| 27 | | | | | | | DNNA | 0.0927 | 0.7782 | 0.1523 | 0.7418 |
| 28 | | | | | | | Sine | 0.0392 | 0.9990 | 0.6158 | 0.5939 |
| 29 | | 2 | 5 | 2 | 50000 | N-C-D E 5 | Seigmoid | 0.0590 | 0.9992 | 0.1834 | 0.7898 |
| 30 | | | | | | E 10 | | 0.0447 | 0.9859 | 0.1782 | 0.7968 |
| 31 | | | | | | E 20 | | 0.0430 | 0.7976 | 0.1750 | 0.7995 |
| 32 | | | | | | E 25 | | 0.0410 | 0.9535 | 0.1745 | 0.7993 |
| 33 | | | | | | E 30 | | 0.0456 | 0.9876 | 0.1740 | 0.7989 |
| 34 | | | | | | E 35 | | 0.0449 | 0.7778 | 0.1736 | 0.7981 |
| 35 | | 2 | 5 | 2 | 50000 | η 0.20 | | 0.0452 | 0.9881 | 0.1735 | 0.7978 |
| 36 | | | | | | η 0.30 | | 0.0452 | 0.9881 | 0.1740 | 0.7989 |
| 37 | | | | | | η 0.50 | | 0.042 | 0.9885 | 0.1729 | 0.7962 |
| 38 | | | | | | η 0.60 | | 0.4068 | 0.9872 | 0.1746 | 0.7994 |
| 39 | | | | | | η 0.90 | | 0.0449 | 0.9879 | 0.1901 | 0.7803 |
| 40 | | 2 | 5 | 2 | 50000 | α 0.1 | | 0.0509 | 0.9860 | 0.1737 | 0.7849 |
| 41 | | | | | | α 0.2 | | 0.0469 | 0.9872 | 0.1732 | 0.7962 |
| 42 | | | | | | α 0.4 | | 0.0449 | 0.9880 | 0.1754 | 0.7993 |
| 43 | | | | | | α 0.5 | | 0.0442 | 0.9883 | 0.1771 | 0.7987 |
| 44 | | | | | | α 0.6 | | 0.0465 | 0.9870 | 0.1772 | 0.7976 |
| 45 | | 2 | 5 | 2 | 52240 | N-C-D | | 0.0307 | 0.9927 | 0.1741 | 0.7989 |
| 46 | | | | | 53440 | | | 0.0256 | 0.9954 | 0.1742 | 0.7988 |
| 47 | | | | | 57340 | | | 0.0282 | 0.9950 | 0.1744 | 0.7985 |
| 48 | 12 S2 | 2 | 5 | 2 | 50000 | N-C-D | Seigmoid | 0.2553 | 0.8662 | 0.1550 | 0.8415 |
| 49 | | | | | 50200 | | | 0.0511 | 0.9886 | 0.1550 | 0.8415 |
| 50 | | | | | 50400 | | | 0.0281 | 0.9975 | 0.1550 | 0.8415 |
| 51 | | | | | 50600 | | | 0.0194 | 0.9908 | 0.1551 | 0.8412 |
| 52 | | 2 | 5 | 1 | 50000 | N-C-D | | 0.0102 | 0.9858 | 0.1526 | 0.8476 |
| 53 | | | | | 50300 | | | 0.0701 | 0.9999 | 0.1527 | 0.8474 |
| **54** | | | | | 50800 | | | **0.0112** | **0.9999** | **0.1522** | **0.8484** |
| 55 | | | | | 51600 | | | 0.0086 | 0.9976 | 0.1525 | 0.8478 |
| 56 | | 1 | 5 | 0 | 50000 | N-C-D | | 0.1136 | 0.9815 | 0.1613 | 0.8262 |
| 57 | | | | | 50300 | | | 0.0270 | 0.9904 | 0.1613 | 0.8262 |
| 58 | | 1 | 4 | 0 | 50500 | | | 0.0135 | 0.9981 | 0.1562 | 0.8383 |
| 59 | | 1 | 2 | 0 | 51250 | | | 0.0381 | 0.9986 | 0.1590 | 0.8317 |
| 60 | | 0 | 0 | 0 | 54600 | | | 0.0851 | 0.9930 | 0.1781 | 0.7830 |

Table 6.3 continues

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 61 | 7 S3 | 2 | 5 | 1 | 50000 | N-C-D | Seigmoid | 0.0123 | 0.9955 | 0.1796 | 0.7821 |
| 62 | | | | | 50300 | | | 0.0198 | 0.9997 | 0.1796 | 0.7821 |
| 63 | | | | | 50500 | | | 0.0144 | 0.9962 | 0.1795 | 0.7822 |
| 64 | | 1 | 5 | 0 | 50700 | | | 0.0549 | 0.9930 | 0.1699 | 0.8048 |
| 65 | | 1 | 4 | 0 | 51000 | | | 0.0878 | 0.9981 | 0.1683 | 0.8089 |
| 66 | | 1 | 2 | 0 | 55006 | | | 0.0126 | 0.9995 | 0.1696 | 0.8060 |
| 67 | | 1 | 1 | 0 | 51916 | | | 0.0191 | 0.9928 | 0.1729 | 0.7983 |
| 68 | | 0 | 0 | 0 | 53400 | | | 0.0780 | 0.9698 | 0.1778 | 0.7844 |

16. Inputs in S3 (seven bidding variables indicated in column 7 of Table 6.2) were used in models B. net 61 to 63, which have two hidden layers with five PEs in the first one and one PE in the second.
17. Only one hidden layer is used with 5, 4, 2, 1 PEs in models B. nets 64 to 67. Many attempts were made to get the best performance of each one of these models by different training iterations before recording the results of training and testing in Table 6.3.
18. Finally, model B. net 68 was designed and trained without any hidden nodes.

The percentage of incorrect recommendations (PWD) made by each model of the examined sixty eight models was produced and recorded in column 7 of Table 6.4. Although there are an endless number of modification options, the procedure explained above helped to produce networks with high performance in both training and testing stages. Selecting the best model from the models tested during the modification process is explained in the following section.

### 6.4.1.6 Model Selection

This section deals with the selection of the best model. The selection process is based on the following criteria:

- High performance in the training stage (low $RMS_{Train}$ and high $R^2_{Train}$);
- High generalisation ability (low $RMS_{Test}$ and high $R^2_{Test}$); and
- Small number of wrong recommendations (low PWD).

An index called the performance index (PI) was developed to help in selecting the best model in a systematic way. The performance index is produced using the following formula:

$$PI = \frac{(R^2{}_{Train} + R^2{}_{Test}) - (RMS_{Train} + RMS_{Test}P + PWD)}{2} \quad (6.1)$$

All the selection criteria adopted are included in equation 6.7, which was designed so the perfect model will have a performance index equal to 1. Although the training sample (162 projects) is quite larger than the test sample (20 projects), the test results have more influence in setting the performance index than the training results. This was allowed because testing is more important than training when assessing the model validity. This is to encourage good generalisation ability and to avoid overfitting, i.e. over training, (Hegazy and Ayed, 1998).

The PI is produced for all the sixty eight models experimented with during the optimisation process (column 8 of Table 6.4). Model B. net 54 has the highest performance index (PI = 0.8175). This model miss-predicted the actual "bid/no bid" decision in one out of twenty bidding situations. This model was selected as the best ANN "bid/no bid" model. Additionally, model B. net 54 has another advantage compared to models B. net1 to 44. The model uses few inputs (12 compared to 19). Model B. net 46 is the best model that uses the same nineteen bidding variables that were used in the parametric model developed in Chapter 8. This model miss-predicted the actual "bid/no bid" decisions in two out of twenty bidding situations. But, a "bid" recommendation was not the desired one as the bid of the corresponding project was rejected in real life by the client. This reduced the accuracy of model B.net 46 from 90% to 85% (the same accuracy performed by the parametric model).

The next section provides a detailed description of the selected ANN "bid/no bid" model.

Table 6.4: Selection of the best ANN "bid/no bid" model

| B. net | No. of Inputs | Training | | Testing | | Wrong Decisions (%) | Performance Index (PI) |
|---|---|---|---|---|---|---|---|
| | | RMS | $R^2$ | RMS | $R^2$ | | |
| 1 | 19 | 0.1022 | 0.8491 | 0.1658 | 0.7983 | 0.15 | 0.6147 |
| 2 | | 0.1183 | 0.8938 | 0.1678 | 0.7856 | 0.10 | 0.6467 |
| 3 | | 0.0869 | 0.9469 | 0.166 | 0.7823 | 0.15 | 0.6632 |
| 4 | | 0.1477 | 0.9365 | 0.1654 | 0.7844 | 0.15 | 0.6289 |
| 5 | | 0.1234 | 0.9308 | 0.1681 | 0.7797 | 0.15 | 0.6345 |
| 6 | | 0.0579 | 0.9836 | 0.1661 | 0.7820 | 0.15 | 0.6958 |
| 7 | | 0.0860 | 0.8574 | 0.1667 | 0.7824 | 0.15 | 0.6186 |
| 8 | | 0.1322 | 0.9710 | 0.1762 | 0.7989 | 0.10 | 0.6808 |
| 9 | | 0.0451 | 0.9668 | 0.1758 | 0.7991 | 0.10 | 0.7225 |
| 10 | | 0.0451 | 0.9668 | 0.1758 | 0.7991 | 0.10 | 0.7035 |

Table 6.4 continues

| B. net | No. of Inputs | Training | | Testing | | Wrong Decisions (%) | Performance Index (PI) |
|---|---|---|---|---|---|---|---|
| | | RMS | $R^2$ | RMS | $R^2$ | | |
| 11 | 19 | 0.0872 | 0.8959 | 0.1688 | 0.7890 | 0.15 | 0.6395 |
| 12 | | 0.0717 | 0.9818 | 0.1669 | 0.7960 | 0.65 | 0.4446 |
| 13 | | 0.0863 | 0.9880 | 0.1745 | 0.7991 | 0.15 | 0.6882 |
| 14 | | 0.1696 | 0.9012 | 0.1731 | 0.7906 | 0.10 | 0.6246 |
| 15 | | 0.1006 | 0.9689 | 0.1699 | 0.7876 | 0.15 | 0.6680 |
| 16 | | 0.0641 | 0.8860 | 0.1759 | 0.7649 | 0.15 | 0.6305 |
| 17 | | 0.1603 | 0.9464 | 0.1730 | 0.7912 | 0.15 | 0.6272 |
| 18 | | 0.0657 | 0.9761 | 0.1708 | 0.7891 | 0.15 | 0.6894 |
| 19 | | 0.0772 | 0.9424 | 0.1696 | 0.7836 | 0.15 | 0.6646 |
| 20 | | 0.0301 | 0.9874 | 0.1985 | 0.7673 | 0.10 | 0.7131 |
| 21 | | 0.0218 | 0.9926 | 0.1994 | 0.7693 | 0.10 | 0.7204 |
| 22 | | 0.0620 | 0.8984 | 0.1706 | 0.7849 | 0.10 | 0.6754 |
| 23 | | 0.2329 | -0.0010 | 0.1703 | 0.0008 | 0.15 | -0.2767 |
| 24 | | 0.1559 | 0.7116 | 0.1175 | 0.6037 | 0.65 | 0.1960 |
| 25 | | 0.3284 | 0.8242 | 0.4241 | 0.7509 | 0.50 | 0.1613 |
| 26 | | 0.0175 | 0.9998 | 0.6022 | 0.7227 | 0.30 | 0.4014 |
| 27 | | 0.0927 | 0.7782 | 0.1523 | 0.7418 | 0.15 | 0.5625 |
| 28 | | 0.0392 | 0.9990 | 0.6158 | 0.5939 | 0.65 | 0.1440 |
| 29 | | 0.0590 | 0.9992 | 0.1834 | 0.7898 | 0.25 | 0.6483 |
| 30 | | 0.0447 | 0.9859 | 0.1782 | 0.7968 | 0.10 | 0.7299 |
| 31 | | 0.0430 | 0.7976 | 0.1750 | 0.7995 | 0.10 | 0.6396 |
| 32 | | 0.0410 | 0.9535 | 0.1745 | 0.7993 | 0.10 | 0.7187 |
| 33 | | 0.0456 | 0.9876 | 0.1740 | 0.7989 | 0.10 | 0.7335 |
| 34 | | 0.0449 | 0.7778 | 0.1736 | 0.7981 | 0.10 | 0.6287 |
| 35 | | 0.0452 | 0.9881 | 0.1735 | 0.7978 | 0.10 | 0.7336 |
| 36 | | 0.0452 | 0.9881 | 0.1740 | 0.7989 | 0.10 | 0.7339 |
| 37 | | 0.0420 | 0.9885 | 0.1729 | 0.7962 | 0.10 | 0.7349 |
| 38 | | 0.4068 | 0.9872 | 0.1746 | 0.7994 | 0.10 | 0.5526 |
| 39 | | 0.0449 | 0.9879 | 0.1901 | 0.7803 | 0.10 | 0.7166 |
| 40 | | 0.0509 | 0.9860 | 0.1737 | 0.7849 | 0.10 | 0.7232 |
| 41 | | 0.0469 | 0.9872 | 0.1732 | 0.7962 | 0.10 | 0.7317 |
| 42 | | 0.0449 | 0.9880 | 0.1754 | 0.7993 | 0.10 | 0.7335 |
| 43 | | 0.0442 | 0.9883 | 0.1771 | 0.7987 | 0.10 | 0.7329 |
| 44 | | 0.0465 | 0.9870 | 0.1772 | 0.7976 | 0.10 | 0.7305 |
| 45 | | 0.0307 | 0.9927 | 0.1741 | 0.7989 | 0.10 | 0.7434 |
| 46 | | 0.0256 | 0.9954 | 0.1742 | 0.7988 | 0.10 | 0.7472 |
| 47 | | 0.0282 | 0.9950 | 0.1744 | 0.7985 | 0.05 | 0.7705 |
| 48 | 12 | 0.2553 | 0.8662 | 0.1550 | 0.8415 | 0.05 | 0.6237 |
| 49 | | 0.0511 | 0.9886 | 0.1550 | 0.8415 | 0.05 | 0.7870 |
| 50 | | 0.0281 | 0.9975 | 0.1550 | 0.8415 | 0.05 | 0.8030 |
| 51 | | 0.0194 | 0.9908 | 0.1551 | 0.8412 | 0.05 | 0.8038 |
| 52 | | 0.0102 | 0.9858 | 0.1526 | 0.8476 | 0.05 | 0.8103 |
| 53 | | 0.0701 | 0.9999 | 0.1527 | 0.8474 | 0.05 | 0.7873 |
| **54** | | **0.0112** | **0.9999** | **0.1522** | **0.8484** | **0.05** | **0.8175** |
| 55 | | 0.0086 | 0.9976 | 0.1525 | 0.8478 | 0.05 | 0.8172 |
| 56 | | 0.1136 | 0.9815 | 0.1613 | 0.8262 | 0.05 | 0.7414 |
| 57 | | 0.0270 | 0.9904 | 0.1613 | 0.8262 | 0.05 | 0.7892 |
| 58 | | 0.0135 | 0.9981 | 0.1562 | 0.8383 | 0.05 | 0.8084 |
| 59 | | 0.0381 | 0.9986 | 0.159 | 0.8317 | 0.10 | 0.7666 |
| 60 | | 0.0851 | 0.9930 | 0.1781 | 0.7830 | 0.10 | 0.7064 |
| 61 | 7 | 0.0123 | 0.9955 | 0.1796 | 0.7821 | 0.10 | 0.7429 |
| 62 | | 0.0198 | 0.9997 | 0.1796 | 0.7821 | 0.10 | 0.7412 |
| 63 | | 0.0144 | 0.9962 | 0.1795 | 0.7822 | 0.15 | 0.7173 |
| 64 | | 0.0549 | 0.9930 | 0.1699 | 0.8048 | 0.15 | 0.7115 |
| 65 | | 0.0878 | 0.9981 | 0.1683 | 0.8089 | 0.15 | 0.7005 |
| 66 | | 0.0126 | 0.9995 | 0.1696 | 0.8060 | 0.15 | 0.7367 |
| 67 | | 0.0191 | 0.9928 | 0.1729 | 0.7983 | 0.15 | 0.7246 |
| 68 | | 0.0780 | 0.9698 | 0.1778 | 0.7844 | 0.15 | 0.6742 |

Fig. 6.18 shows the performance indices of the tested models and indicates the selected model (B. net 54).

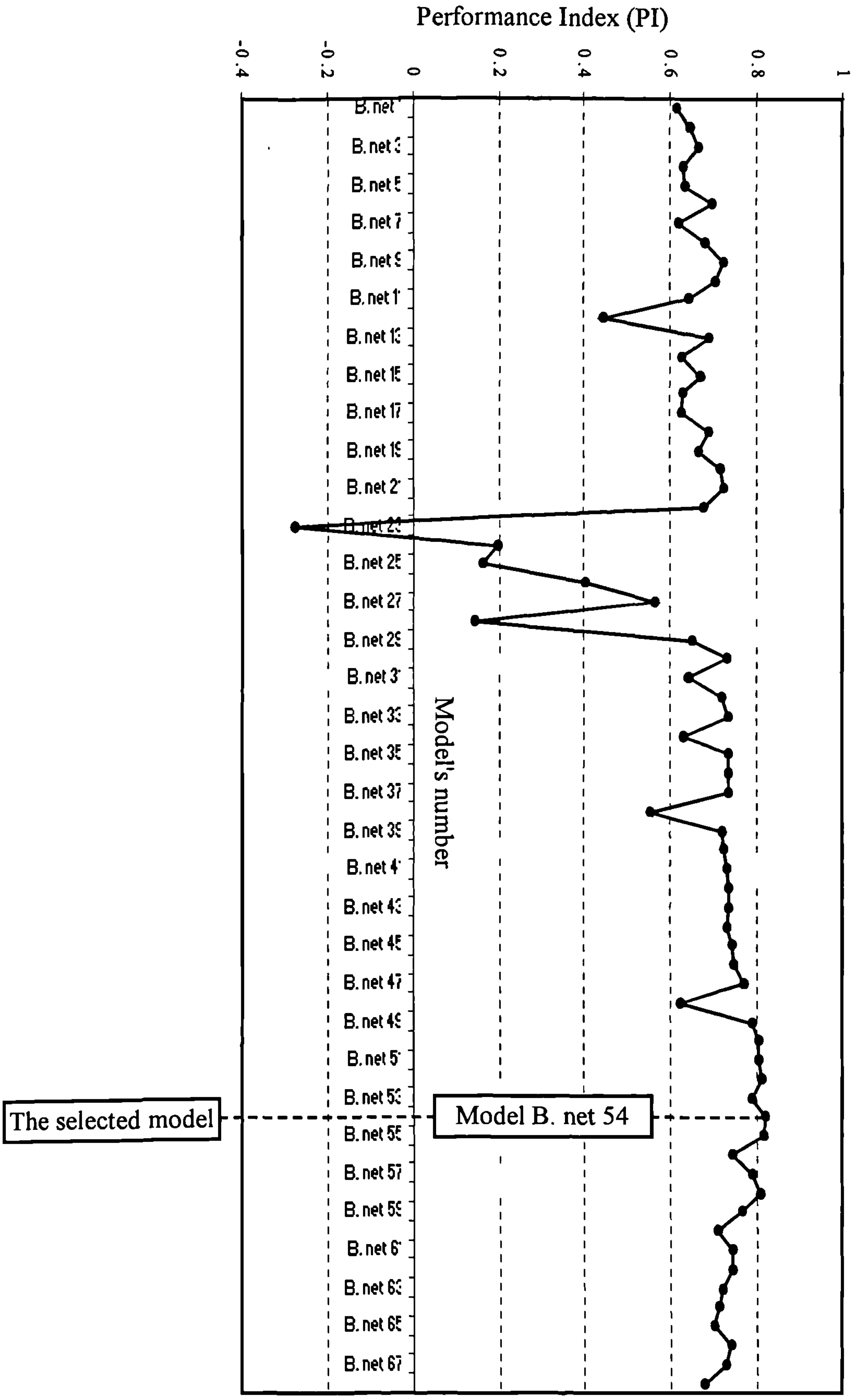



Fig. 6.18: Selection of the best ANN "bid/no bid" model

### 6.4.2 The Selected ANN "Bid/No Bid" Model

This section illustrates the topology of the selected model (B. net 54) and provides all the parameters used in scaling/de-scaling the inputs and outputs, training parameters, and the final connection weights.

Model B. net 54 is structured from the following layers:

1. Input layer (*I*) containing twelve nodes for the twelve bidding variables contained in S2 (column 5 of Table 6.2) and a bias node (f0). The input nodes are fully connected to the next layer. The bias node is connected to all the subsequent layers;
2. Hidden layer (*J*) containing five processing elements with sigmoid transfer function. All these PEs are fully connected to the second hidden layer;
3. Hidden layer (*K*) containing one processing element with sigmoid transfer function. This PE is connected to the output layer; and,
4. Output layer (*O*) containing one output PE with sigmoid transfer function.

The architecture of this model is illustrated in Fig. 6.19.

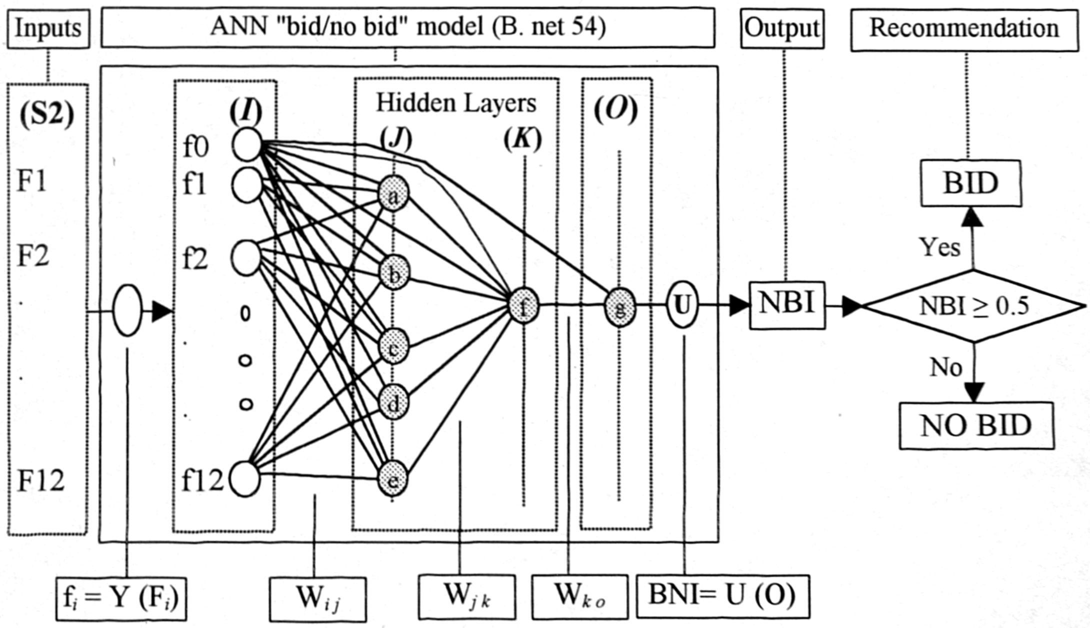



Fig. 6.19: Structure of the final ANN " bid/no bid" model

Table 6.5 summarises the main characteristics of the final ANN "bid/no bid" model. The values of the "MinMax Table" extracted automatically form the training input output file are shown in Table 6.6.

Table 6.5: Main characteristics of model (B. net 54)

| L.Coef | Momentum | Transfer Function | Learning Rule | Epoch size | Network Ranges | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Inputs | | Output | |
| | | | | | Min | Max | Min | Max |
| 0.3, 0.2, 0.15 | 0.500 | Sigmoid | N-C-D | 5 | -1 | +1 | 0.20 | 0.80 |

Table 6.6: The "MinMax Table" used in model B. net 54

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 | F10 | F11 | F12 | Output |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Min | 2 | 1 | 1 | 1 | 2 | 1 | 2 | 1 | 0 | 1 | 0 | 1 | 0 |
| Max | 6 | 6 | 6 | 5 | 6 | 5 | 6 | 6 | 5 | 5 | 6 | 5 | 1 |

The connection weights were extracted manually form model B. net 54 and arranged in Table 6.7. Where (a, b, c, d, e, f, and g) are the hidden and the output processing elements of the final ANN "bid/no bid" model and (f0, f1, f2, ...., and f12) are the input nodes of this model (see Fig. 6.18)

Table 6.7: Connection weights between the processing elements of model B. net54

| | | | a | b | c | d | e |
|---|---|---|---|---|---|---|---|
| | | f1 | -0.88027 | -0.42170 | 0.96278 | -0.97451 | -1.32513 |
| | | f2 | -1.00311 | -0.45671 | 1.48411 | -1.35538 | -2.19275 |
| | | f3 | -0.96633 | -0.55296 | 0.71179 | -0.88578 | -1.21022 |
| | | f4 | -0.63949 | -0.28576 | 0.33895 | -0.51809 | -1.03607 |
| | | f5 | -0.49016 | -0.22731 | 0.73671 | -0.78143 | -0.96878 |
| | | f6 | -1.07394 | -0.67374 | 1.08228 | -1.26194 | -1.06969 |
| | | f7 | -0.64813 | -0.09494 | 0.98135 | -1.23332 | -0.92132 |
| | | f8 | -0.45521 | -0.14217 | 0.37644 | -0.48314 | -0.56726 |
| | | f9 | 0.34733 | 0.26289 | -0.29875 | 0.33563 | 0.45891 |
| | | f10 | -0.18849 | 0.02979 | 0.34784 | -0.10771 | -0.36222 |
| | | f11 | -0.09521 | 0.17298 | -0.28822 | 0.11747 | -0.07632 |
| | | f12 | -1.02560 | -0.56259 | 1.14928 | -0.97105 | -1.61119 |
| | | f0 = +1 | -0.409355 | -0.286996 | +0.402020 | -0.45730 | -0.53781 |
| | f | +0.99327 | -1.502217 | -0.557653 | +2.370710 | -1.896123 | -2.64172 |
| g | +2.99174 | -1.45017 | | | | | |

The values of the "MinMax Table" and the network target ranges were used to produce the scaling formulas used by the selected model (Equation D.1/Appendix D). These formulas are listed in Table 6.8.

Table 6.8: Scaling the input real-world values to the desired values

| No. | Factor Name | Desired (Scaled) values ($f_i$) | Equation No. |
|---|---|---|---|
| F1 | Fulfilling the to-tender conditions | 0.5 * F1 -2.0 | (6.2) |
| F2 | Site accessibility | 0.4 * F2 -1.4 | (6.3) |
| F3 | Site clearance of obstructions | 0.4 * F3 -1.4 | (6.4) |
| F4 | Availability of capital required | 0.5 * F4 -1.5 | (6.5) |
| F5 | Availability of materials required | 0.5 * F5 -2 | (6.6) |
| F6 | Proportions that could be constructed mechanically | 0.5 * F6 -1.5 | (6.7) |
| F7 | Confidence in the cost estimate | 0.5* F7 -2 | (6.8) |
| F8 | Financial capability of the client | 0.4 * F8 -1.4 | (6.9) |
| F9 | Public objection | 0.4 * F9 -1.0 | (6.10) |
| F10 | Current work load | 0.5 * F10 -1.5 | (6.11) |
| F11 | Relation with/ reputation of the client | 0.3333 * F11 -1 | (6.12) |
| F12 | Favourability of the cash flow | 0.5 * F12 -1.5 | (6.13) |

The formula used in the model to de-scale the scaled output values to real world values is as follows (Equation D.2/Appendix D):

Final output (NBI) = 1.666667 * scaled output (*O*) - 0.33333 (6.14)

The developed ANN "bid/no bid" model in its current statues is not a user-friendly model. It requires some skills in operating the NeuralWorks software. To solve this problem, the connection weights, the scaling formulas (6.2 to 6.13), and the de-scaling formula (6.14) can be used easily to develop a user-friendly spreadsheet prototype. The following section explains how the quality of the model output was improved by developing a complementary model that produces a degree of confidence for each "bid/no bid" recommendation. This improves the user acceptance of the model output.

#### 6.4.2.1 Degree of Confidence

During the optimisation phase, the cut-off point between the "bid" and " no bid" recommendations was initially adopted as (NBI = 0.5), i.e. the midpoint between the actual "bid" (1) and "no bid" (0). This limit might not be the optimum one. This section explains a simple procedure used to set this cut-off point to its best limit (X) and to select another two parameters (X1 and X2) to be used in developing the confidence model. Fig. 6.20 illustrates the relationship between the "bid/no bid" decision and X, X1, and X2.

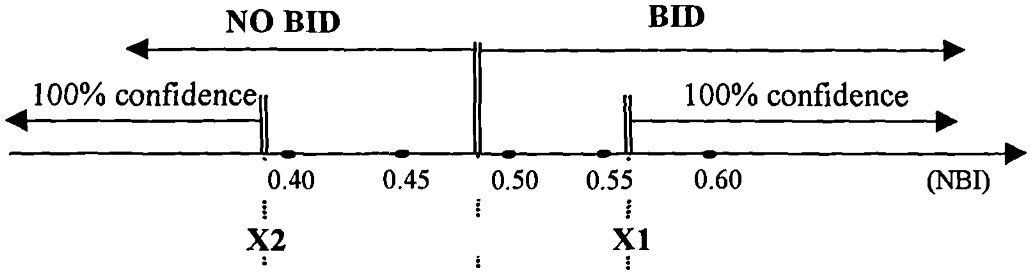



Fig. 6.20: Parameters of the "Bid/no bid" decision

Where:

- X is the limit above which the model will recommend "bid" and below which the model will recommend "no bid";
- X1is the limit above which the model will recommend "bid" with 100% degree of confidence, i.e. 0% confidence in "no bid"; and,
- X2 is the limit below which the model will recommend "no bid" with 100% degree of confidence, i.e. 0% confidence in "bid".

To select values for these parameters, model (B. net 54) was used to produce neural bidding indices for the real projects used included in the modelling sample. Different values were experimented with for the cut-off point (X). The number of unsuccessful recommendations was recorded for each experiment as shown in Table 6.9.

Table 6.9: Setting the best cut-off point between "bid" and "no bid" spaces

| X | | 0.1 | 0.2 | 0.3 | 0.4 | 0.45 | 0.5 | 0.55 | 0.6 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Unsuccessful decisions | Train | 10 | 10 | 9 | 9 | 8 | 6 | 6 | 6 | 8 | 10 | 19 |
| | Test | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 3 |

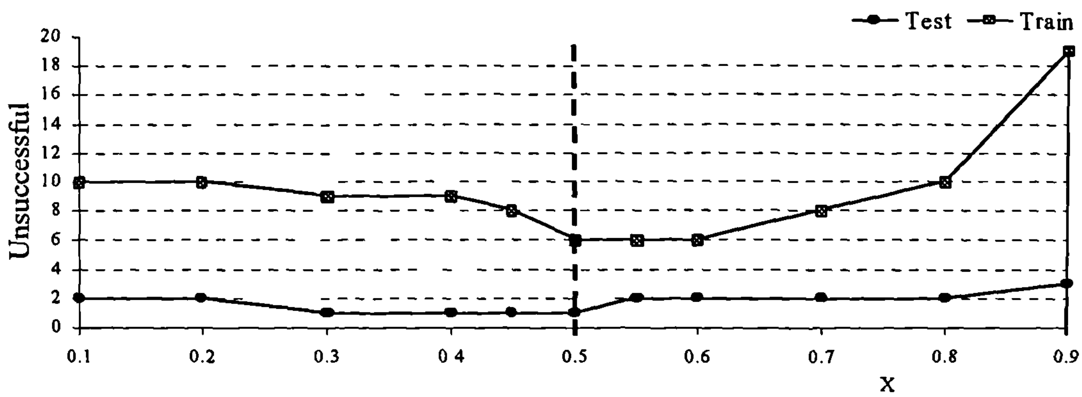



Fig. 6.21: The best cut-off point between "bid" and "no bid"

The minimum number of unsuccessful recommendations corresponds to three values of X (0.5, 0.55, and 0.6). The value (X= 0.50) was selected as the optimum limit between the "bid" and "no bid" recommendations because it, also, corresponds to the minimum number of unsuccessful recommendations for the testing projects as shown in Fig. 6.21. By adopting this limit, the model will recommend the "bid" decision when (NBI $\geq$ 0.50).

Examining the neural bidding indices produced for the training situations revealed that all contractors decided to bid when NBI $\geq$ 0.962, which was considered to be $X_1$. On the other hand, all contractors decided not to bid when NBI $\leq$ 0.218, which was considered to be $X_2$.

The degree of confidence between NBI = 0.218 and NBI = 0.50 and between NBI = 0.50 and NBI = 0.962 was considered to be a linear function. Thus, using X, $X_1$ and $X_2$, a confidence model was developed as illustrated in Fig. 6.22, which can be explained as follows:

- If NBI $\geq$ 0.962, then "bid" with Cb = 100%;
- If 0.50 < NBI < 0.962, then "bid" with the following degree of confidence:

$$Cb = 50 + \frac{50 * (NBI - 0.50)}{0.962 - 0.50}$$

$$Cb = 107.9914 * NBI - 3.9957 \qquad (6.15)$$

- If NBI = 0.50, then "bid" with Cb = 50%,
- If 0.50 < NBI < 0.218, then "no bid" with the following confidence degree:

$$Cnb = 50 + \frac{50 * (0.50 - NBI)}{0.50 - 0.218}$$

$$Cnb = -177.305 * NBI + 138.6525 \qquad (6.16)$$

- If NBI $\leq$ 0.218, then "no bid" with Cnb = 100%; and,

- Cb = 100 - Cnb (6.17)

Where:

Cb is the degree of confidence in "bid" recommendation; and,

Cnb is the degree of confidence in "no bid" recommendation.

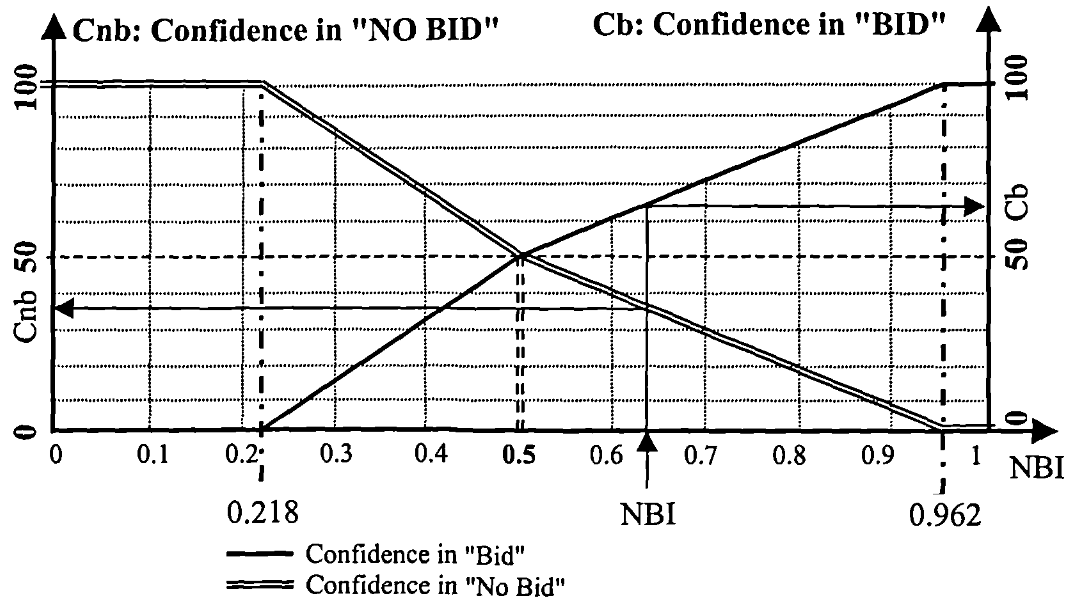



Fig. 6.22: Confidence degrees in "bid" and "no bid"

### 6.4.2.2 The Effect of Input Variables on The "Bid/no bid" Decision

The "black box" feature of the ANN models makes it very difficult to assess the influence of each input variable on their output(s). However, an attempt was made to find out how the ANN "bid/no bid" model will response to changes in each one of its input variables. To simplify this task, a set of input values for which the degree of confidence in both "bid" and "no bid" recommendations is equal to 50%, i.e. mid-point Sanrio was developed. This makes it easier to notice the influence of any change in an individual input variable. As explained in section 4.5.1.7, neutral values, i.e. scores, ($B_i/B_j$) were developed for the "bid/no bid" factors (based on the findings of questionnaire A). It is assumed that when the contractor's assessment of a bidding factor ($F_i$) is equal to its neutral score ($B_i$), it neither encourages nor discourages the "bid" recommendation. The parametric model developed in Chapter 5 was based on this assumption so it produces a bidding index (BI) equal to zero when all its inputs are assessed by their neutral scores (see section 5.3.3). The ANN "bid/no bid" model was tested using the same neutral values. The recommendation was "bid" with 78,37% degree of confidence, which is higher than 50%. This demonstrates that the ANN model is more willing the recommend the "bid" decision compared to the parametric model.

However, these neutral values ($B_i$) can be modified to get the desired values ($B'_i$) for which the ANN model will produce 50% degree of confidence in both "bid" and "no bid" recommendations. The following formula was used to modify the original neutral values:

$$B'_i = B_i + a*S_i \qquad (6.18)$$

Where:

$B'_i$: is the new neutral score where factor ($F_i$) has no effect on the recommendation of the ANN "bid/no bid" model;

$B_i$: is the original neutral score, which is the mean of values suggested by Syrian contractors for factor $F_i$ as response to questionnaire A (see section 5.5.1.7);

a: is a constant; and;

$S_i$: the standard deviation of the suggested values for the neutral score of factor $F_i$ (see Tables 5.6 and 5.7).

The constant (a) was identified through a trial and error process. It was found that (a = - 0.14846) corresponds to the required neutral values ($B'_i$), which are listed in column 3 of Table 6.10. The neural bidding index (NBI) produced for these values by the ANN model is (0.5), i.e. the degree of confidence in both "bid" and " no bid" recommendations is 50%. To uncover the ANN model's response to changes in its inputs, each input was assigned three scores (0, 3, and 6) while setting the other inputs to their neutral scores ($B'_i$). First, factor (F1) was assigned a (0) score, i.e. extremely low, while setting the other factors to their neutral scores ($B'_i$). The corresponding output of the ANN model (NBI) was recorded in columns 4 of Table 6.10. Then scores 3 (medium) and 6 (extremely high) were tested and the results were recorded in column 5 and 6 respectively. The same process was repeated for all the input variables. It was believed that the difference between the NBIs for (0) and (6) scores assigned to an input variable ($F_i$) indicates the sensitivity of the model output to changes in this variable. Therefore, an index called the sensitivity index (SI) was computed for each input variable ($F_i$) using the following equation:

$$SI_i = NBI(6)_i - NBI(0)_i \qquad (6.19)$$

The sensitivity indices are listed in the last column of Table 6.10 and illustrated in Fig. 6.23.

Table 6.10: Sensitivity of the ANN model output to changes in individual inputs

| No. | Factor Description | Neutral Score | NBI (0) | NBI (3) | NBI (6) | SI |
|---|---|---|---|---|---|---|
| F1 | Fulfilling the to-tender conditions | 5.79 | -0.011 | 0.017 | 0.553 | 0.564 |
| F2 | Site accessibility | 2.85 | 0.004 | 0.500 | 0.976 | 0.972 |
| F3 | Site clearance of obstructions | 3.51 | 0.024 | 0.347 | 0.882 | 0.858 |
| F4 | Availability of capital required | 3.30 | 0.055 | 0.416 | 0.858 | 0.803 |
| F5 | Availability of materials required | 3.43 | 0.027 | 0.365 | 0.888 | 0.861 |
| F6 | Proportions that could be constructed mechanically | 2.94 | 0.007 | 0.482 | 0.972 | 0.965 |
| F7 | Confidence in the cost estimate | 3.74 | 0.006 | 0.263 | 0.902 | 0.896 |
| F8 | Financial capability of the client | 3.35 | 0.155 | 0.443 | 0.754 | 0.599 |
| F9 | Public objection | 2.04 | 0.685 | 0.420 | 0.184 | -0.501 |
| F10 | Current work load | 2.79 | 0.274 | 0.508 | 0.720 | 0.446 |
| F11 | Relation with/ reputation of the client | 3.73 | 0.563 | 0.514 | 0.462 | -0.101 |
| F12 | Favourability of the cash flow | 2.64 | 0.088 | 0.576 | 0.982 | 0.894 |

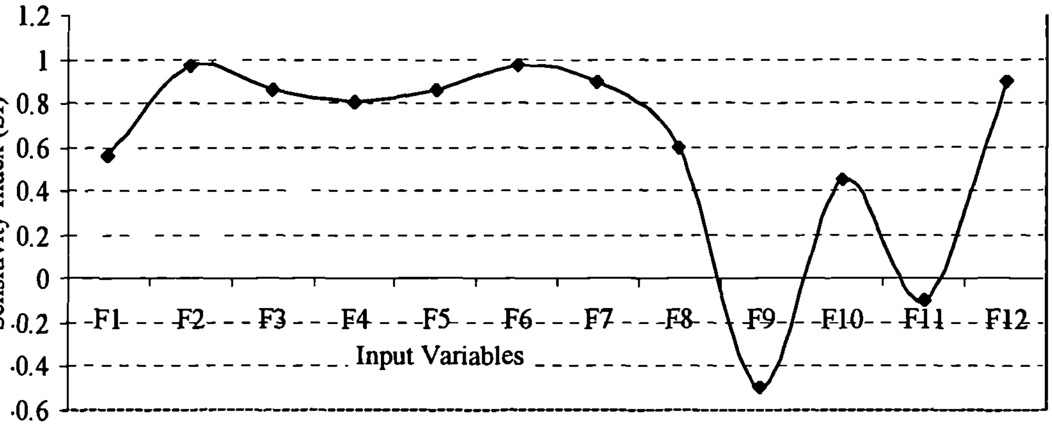



Fig. 6.23: Effect of individual inputs on the ANN "bid/no bid" model's output

Unexpectedly, the first variable (fulfilling the to-tender conditions), which has the highest correlation coefficient with the "bid/no bid" decision (see Table 6.2) and the highest importance index (see Table 4.4) has only a moderate effect on the output of the ANN "bid/no bid" model as shown in Fig. 6.22. Also, Table 6.10 shows that there is only a very small difference between the NBIs for (0) and (3) scores of this variable. This may be attributed to the absence of low scores (between 0 and 3) of this variable in the input space of the training sample (see Appendix E). The model failure to capture the full effect of such critical variable is one of its drawbacks. Another variables affect the model's output not in the way acknowledged in the current bidding practice. These include the following:

- High current workload (F10) will encourage the "bid" recommendation for new projects; and,
- Good relation with and reputation of a client slightly encourages the "no bid" recommendation for projects with him/her.

Nevertheless, the developed ANN "bid/no bid" model has a good ability to generalise solutions for unforeseen bidding situations as demonstrated in the following section.

#### 6.4.2.3 Testing and Validation

Twenty bidding situations were randomly selected from one hundred and eighty two real life situations provided by Syrian contractors through questionnaire B and used to test the final ANN "bid/no bid" model. The contractor's assessments were presented to the developed main model, which produced a neural bidding index (NBI) for each bidding situation. The computed NBI was passed to the complementary confidence model to compute the corresponding degree of confidence. Table 6.11 shows the recommendations and the degrees of confidence produced for the twenty test cases. Fig. 6.24 illustrates the actual and predicted decisions of these cases. The model miss-predicted the actual decision for one bidding situation (No. 10) and simulated accurately the actual decisions of all the nineteen situations. But, even though a bid was submitted for project 13, the bid was rejected in real life by the client. The other submitted bids were accepted. Taking this into account and assuming that the contractors made the right decisions in real life, it can be concluded that the model produced the "right", i.e. desired, recommendations in eighteen out of twenty bidding situations, i.e. 90% accuracy. The ANN "bid/no bid" model is slightly more accurate compared to the parametric model developed in Chapter 5, which produced the desired recommendations for 85% of the same test bidding situations. The low confidence degree in the "bid" recommendation made for project (4) may be attributed to many reasons, which include:

- The "to-tender" conditions imposed by the client are not fully met; and,
- The portion that can be constructed mechanically is small.

If the "to-tender" conditions are fulfilled, i.e. scored with 6, and the portion that can be constructed mechanically was score with 3, i.e. medium, the model will recommend to bid with 95.35% confidence.

Table 6.11: Actual and predicted decisions of twenty unforeseen bidding situations.

| Project No. | Actual decision | | NBI | Predicted decision | Confidence degree (%) | Notes |
|---|---|---|---|---|---|---|
| 1 | Bid | 1 | 0.9726 | Bid | 100 | |
| 2 | Bid | 1 | 0.8541 | Bid | 88.24 | |
| 3 | Bid | 1 | 0.9999 | Bid | 100 | |
| 4 | Bid | 1 | 0.5191 | Bid | 52.06 | |
| 5 | Bid | 1 | 0.9291 | Bid | 96.34 | |
| 6 | Bid | 1 | 1.0057 | Bid | 100 | |
| 7 | Bid | 1 | 1.0091 | Bid | 100 | |
| 8 | No Bid | 0 | 0.0542 | No Bid | 100 | |
| 9 | No Bid | 0 | -0.0002 | No Bid | 100 | |
| 10 | No Bid | 0 | 0.9955 | Bid | 100 | Wrong |
| 11 | Bid | 1 | 1.0130 | Bid | 100 | |
| 12 | Bid | 1 | 1.0090 | Bid | 100 | |
| 13 | Bid | 1 | 0.9414 | Bid | 97.67 | Rejected |
| 14 | Bid | 1 | 0.9913 | Bid | 100 | |
| 15 | No Bid | 0 | 0.0528 | No Bid | 100 | |
| 16 | No Bid | 0 | 0.1655 | No Bid | 100 | |
| 17 | No Bid | 0 | -0.0101 | No Bid | 100 | |
| 18 | Bid | 1 | 0.9987 | Bid | 100 | |
| 19 | Bid | 1 | 1.0092 | Bid | 100 | |
| 20 | No Bid | 0 | 0.0007 | No Bid | 100 | |

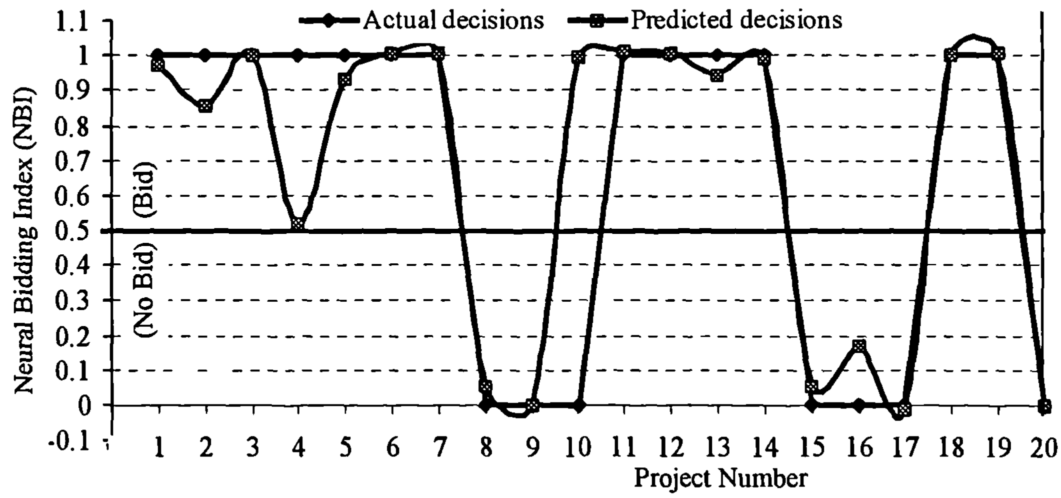



Fig. 6.24: Actual and predicted decisions of the test projects

After finalising the ANN "bid/no bid" model, a similar ANN model was developed for the second part of the bidding process (mark up selection) as explained in the following sections.

## 6.5 Development of ANN Mark up Model

An innovative "bid/no bid" decision-support model was developed in the previous sections using the ANN technique. This model can be very useful particularly to new contractors who have not considerable experience in deciding whether to bid or not on new construction projects. It would be more useful if it is able to help in making another very important decision. This is setting a suitable competitive mark up size when a "bid" decision is made. In Chapter 5, the "mark up selection" process was modelled using regression techniques. The developed regression mark up model proved a good reliability. However, its major limitation is being inconsistent, i.e. small changes in some inputs may cause large change in the output and some times cause unreasonable output. This raised a need to develop a more reliable mark up model. It has been claimed by many researchers such as Moselhi et al (1991) and Li (1996a, 1999) (see section 3.2.2.3) that the neural network technique is a viable tool to help in setting a suitable competitive mark up size. Thus, the ANN technique was considered in this study as a potential solution for the regression mark up drawbacks. The following sections explain the development process of an ANN model to help Syrian contractors in setting a suitable mark up to be added to the total cost of a new construction project if a "bid" decision was made for this project. The main steps of ANN mark up model development are explained briefly in the following section. The same general development methodology used for the "bid/no bid" model (see Fig. 6.2) was used for the mark up model.

### 6.5.1 Data Preprocessing

The mark up was not provided in some of the bidding samples collected through questionnaire B. Only one hundred and eleven cases were qualified to be useful in developing mark up models. Fifteen projects were selected randomly and reserved for the validation stage. The remaining ninety six projects were used in training and optimising the ANN mark up model. The following section explains the selection of the input variables, which is the must important part of the data preprocessing stage.

#### 6.5.1.1 Selection of the Input Variables

It is essential to identify what input factor should be considered in the developed ANN mark up model. It is generally accepted that only the most influential factors need to be considered. Also, the ANN technique, likewise the regression techniques, is build on the assumption that the input variables are independent, i.e. there are not considerable correlation between them. Therefore, the selection of the model inputs was guided by the following conditions:

1. High importance index;
2. High correlation with the mark up size; and,
3. Low correlation with other considered factors.

As explained in Chapters 4, thirty five factors that affect the mark up decision in Syria were identified and ranked according to their importance to Syrian contractors when making this decision (see Table 4.5). Seventeen factors were omitted because they have small importance indices (see Fig 4.13). By performing a simple correlation analysis on the modelling sample (ninety six projects), it was found that only eleven factors have 50% or greater absolute correlation with the mark up size as shown in Table 4.8 and Fig. 4.15. These eleven factors were used in developing the previous regression mark up model because they fulfil the first two selection conditions. But, the question is, do they fulfil the third condition?. It is not expected that they are absolutely independent from each other and it might not be necessary to be as such. Therefore, six sets ($S_1$ to $S_6$) of factors that fulfil the independence condition to different degrees were selected and tested. Table 6.12 shows the result of a correlation analysis carried out to identify the interrelationships between the eleven mark up factors. A factor ($F_i$) was selected from the eleven factors and included in a set ($S_k$) if the following condition was met:

$$| r_{ij} | \geq A_k \qquad (6.20)$$

Where:

$| r_{ij} |$ is the absolute correlation coefficients between factor $F_i$ and all the remaining ten factors ($F_j$); and,

$A_k$ is the cut-off limit chosen for set $S_k$.

If the correlation between any two factors ($F_i$, $F_j$) was ($r_{ij} \geq A_k$), only the one, which has greater correlation with the mark up size is included within $S_k$ and the other factor are omitted. First, to consider all the factors in $S_1$, the cut-off point was set to ($A_1$ =1). Then, to 0.6, 0.55, 0.50, 0.45, and 0.40 for sets $S_2$ to $S_6$. Table 6.13 Shows the factors included in each set of factors as indicated by asterisks. $S_1$ to $S_6$ were considered as potential sets of input variables. Many ANN models were developed for each set as explained in the modification phase. Starting with all the eleven factors ($S_1$), the following section explains the design of the initial model.

### 6.5.2 Initial Design Decisions

The eleven mark up factors included in S1 indicated in column three of Table 6.12 were considered as the input variables of the initial ANN mark up model. The continuos mode was used for these inputs as each one can take a value on a scale from 0 (extremely low) to 6 (extremely high). The continuos mode was also used for the only output variable (mark up percentage). The simplest topology was adopted for the initial model as a starting point. This topology is supposed to be identical to the best liner regression model that can be possibly developed using the same input and output variables. Fig. 6.25 shows the structure of the initial model (M.net1) that is composed of the input buffer containing eleven nodes fully connected to the output layer, which contains only one processing element (PE) for the only output (mark up percentage). The "normalised cumulative delta " learning rule and the sigmoid transfer function were used. The other parameters were set to their default values as shown in Table 6.14.

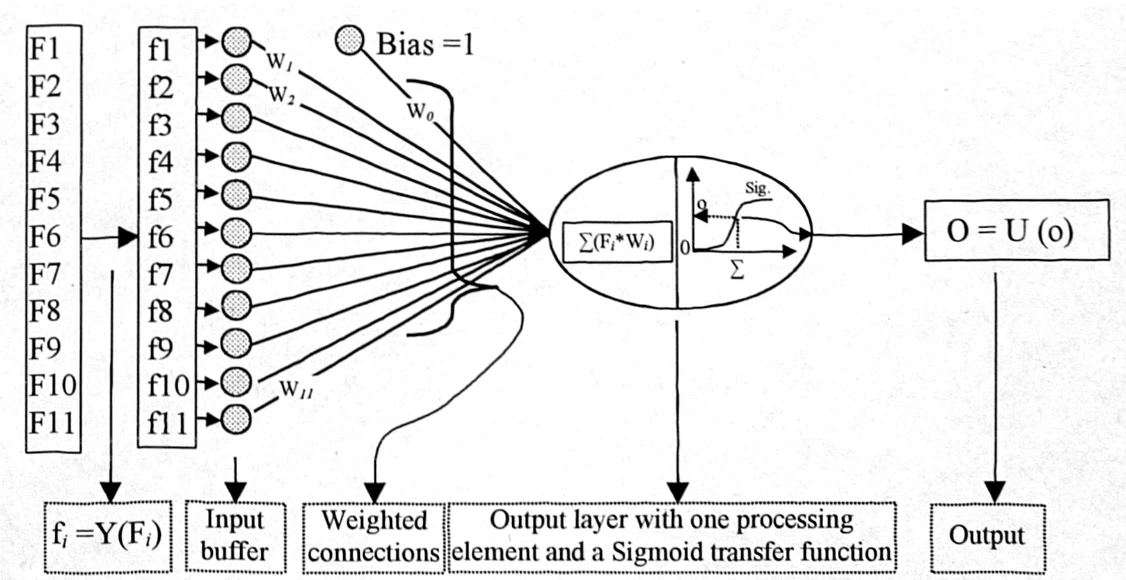



Fig. 6.25: Structure of the initial ANN "mark up" model

Table 6.12: Correlation between the mark up factors

| | RISK | EQUIPOWN | CONFCOST | MATERAVA | COMPETEN | BUILDABI | COMPETIT | MECHANIC | RIGIDITY | CLEAOBST | SITEACCE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| RISK | 1.000 | | | | | | | | | | |
| EQUIPOWN | -0.512 | 1.000 | | | | | | | | | |
| CONFCOST | -0.502 | 0.493 | 1.000 | | | | | | | | |
| MATERAVA | -0.491 | 0.425 | 0.605 | 1.000 | | | | | | | |
| COMPETEN | -0.487 | 0.427 | 0.479 | 0.394 | 1.000 | | | | | | |
| BUILDABI | -0.578 | 0.465 | 0.345 | 0.487 | 0.420 | 1.000 | | | | | |
| COMPETIT | -0.612 | 0.360 | 0.448 | 0.442 | 0.489 | 0.494 | 1.000 | | | | |
| MECHANIC | -0.401 | 0.428 | 0.259 | 0.297 | 0.343 | 0.611 | 0.350 | 1.000 | | | |
| RIGIDITY | 0.494 | -0.431 | -0.511 | -0.576 | -0.311 | -0.588 | -0.305 | -0.426 | 1.000 | | |
| CLEAOBST | -0.624 | 0.460 | 0.449 | 0.299 | 0.354 | 0.237 | 0.371 | 0.253 | -0.270 | 1.000 | |
| SITEACCE | -0.404 | 0.503 | 0.506 | 0.420 | 0.472 | 0.338 | 0.415 | 0.337 | -0.244 | 0.315 | 1.000 |
| **MARK UP** | **0.711** | **-0.636** | **-0.631** | **-0.619** | **-0.614** | **-0.596** | **-0.577** | **-0.544** | **0.533** | **-0.528** | **-0.514** |

Table 6.13: Sets of input variables with different degrees of inter-correlation.

| **No.** | **The most influential mark up factors** | **S1** | **S2** | **S3** | **S4** | **S5** | **S6** |
|---|---|---|---|---|---|---|---|
| 1 | Risks Expected | * | * | * | * | * | * |
| 2 | Availability of equipment owned by the contractor | * | * | * | | | |
| 3 | Confidence in the cost estimate | * | * | * | | | |
| 4 | Availability of materials required | * | | | * | | |
| 5 | Competence of the expected competitors | * | * | * | * | | |
| 6 | Degree of buildability | * | * | | | | |
| 7 | Expected degree of competition (number of competitors) | * | | | | | |
| 8 | Way of construction (mechanically/ manually) | * | | * | * | * | |
| 9 | Rigidity of specifications | * | * | * | | | |
| 10 | Site clearance of obstructions | * | | | | | |
| 11 | Site accessibility | * | * | * | * | * | |

Table 6.14: Parameters of model (M. net1)

| L.Coef | Momentum | Trans. Pt. | F' Offset | Lcoef Ratio | Epoch size | Network Ranges | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Inputs | | Output | |
| | | | | | | Min | Max | Min | Max |
| 0.150 | 0.400 | 10000 | 0.100 | 0.500 | 16 | -1 | +1 | 0.20 | 0.80 |

The initial weights are automatically set to random small numbers between (-0.5) and (+0.5). These weights are fine-toned in the training stage.

### 6.5.3 Training

The initial network connection weights ($W_i$) of model (M. net 1) are random small number between -0.5 and +0.5 set automatically by the NeuralWorks.
The back propagation learning algorithm was used to modify these weights. Fixed number of training iterations (50000) was used in this stage. When the learning counter reaches this limit, the leaning was automatically ceased. The ability of model (M. net1) to explain the variance in the training data after 50000 iterations was presented by its training diagnostic instruments ($RMS_{train}$ = 0.0566 and $R^2_{train}$ = 0.8413). These values were recorded in the Table 6.15. The generalisation capability of this model is explained in the following section.

### 6.5.4 Testing

Fifteen bidding situations reserved for validation were used in this stage. The input values in these cases were presented to model M net1. The produced outputs were compared to the actual ones and two measures of the test result were provided by the NeuralWorks software. These measures ($RMS_{test}$ = 0.0.0538 and $R^2_{test}$ = 0.9113) were recorded in Table 6.15. The following section explains a guided trial and error modification procedure adopted to get the best possible ANN mark up model.

### 6.5.5 Modification

The general modification approach used in the ANN "bid/no bid" modelling (see section 6.4.1.6) was used to produce the best possible ANN mark up model as summarised below:

1. Starting from model "M net 1", many combinations of different number of hidden layers with different number of processing elements (PEs) were tested (M nets 2 to 19). Training and testing results were recorded in Table 2/Appendix D. The structure of model M net 2 (one hidden layer containing five PEs) proved to be more suitable when considering the first set of inputs (S1 in Table 6.13).
2. The same structure was adopted in the subsequent models with different learning rules (M nets 20 to 24). The "delta rule" learning mechanism performed better that the others. Therefore, it was adopted in all subsequent models.
3. In models M net 25 to 28, different transfer functions were tested. The sigmoid proved to be more suitable. Thus, it was used in all of the subsequent models.
4. The delta rule does not use the epoch size (E) when updating the connection weights. Even though, different values of the epoch size were tested (M nets 29 to 33) because the NeuralWorks software uses the epoch size to calculate the RMS and $R^2$ measures during the training process. The epoch size (E = 5) helped to get the lowest RMS and the highest $R^2$ values. Thus it was used in all subsequent models.
5. Model (M net 29) proved the best performance up to this point. Therefore, it was selected and many attempts were made to improve it by more training (M nets 34 to 36).
6. Only the seven input variables included in (S2) where considered. First, the best structure used for (S1) inputs was used (M nets 37 and 38). Then, the number of PEs was reduced to two (M nets 39 and 40) and to none (M bets 41 and 42) as (S2) inputs is smaller than (S1). A hidden layer with five PEs still more suitable.
7. The seven variables included in S3 were used (M nets 43 to 48).
8. Only the five variables included in S4 (see Table 6.13) were considered. First with five hidden PEs (M nets 49 to 52). Then, the number of hidden PEs was reduced to two (M net 53) and to none (M net 54).

9. Three input variables (S5) were considered with five hidden PEs (M net 55), two hidden PEs (M net56), one hidden PE (M net 57), and none hidden PEs (M net 58).
10. Only the "risks expected" factor included in S6 was considered with none hidden PEs (M net 59), one hidden layer containing one PE (M net 60) and two PEs (M net 61), and two hidden layers one PE in each one (M net 62).

The training and testing results in terms of RMS and $R^2$ were recorded in Table 6.15. The next section explains how the best ANN mark up model was selected.

### 6.5.6 Model Selection

Section 6.4.1.7 explained how the best ANN "bid/no bid" was selected using an index called the performance index (PI). A similar index computed by equation (6.21) was used to help in selecting the best ANN mark up model.

$$PI = \frac{(R^2{}_{train} + R^2{}_{test}) - (RMS_{train} + RMS_{test})}{2} \qquad (6.21)$$

The above equation was subjectively designed to produce a performance index (PI =1) for the perfect model, i.e. RMS = 0 and $R^2$ =1 for both of the training and testing samples. The performance index was computed for all the experimented with models (see Table 6.16). Fig 6.26 Illustrates the performance indices of all these models. Model 36 has the highest PI (0.9166). Thus, this model can be considered as the best one. However, there is other important selection criterion that should also be considered. This is the number of the model's inputs. Therefore, the selection process was performed in the following two steps:

Table 6.15: The modification process of developing ANN mark up model

| One output (Mark up percentage) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| M Net | No. Inputs | No. of Hidden Layers | Node's in H.L 1 | Nodes in H.L 2 | Iteration | L.R. | T.F. | Training RMS | Training $R^2$ | Testing RMS | Testing $R^2$ |
| 1 | | 0 | 0 | 0 | | | | 0.0566 | 0.8413 | 0.0538 | 0.9113 |
| 2 | | | 5 | | | | | 0.0592 | 0.9436 | 0.0571 | 0.8989 |
| 3 | | | 10 | | | | | 0.0659 | 0.6648 | 0.0579 | 0.8962 |
| 4 | | 1 | 15 | 0 | | | | 0.0630 | 0.7442 | 0.0569 | 0.9005 |
| 5 | | | 20 | | | | | 0.0586 | 0.7951 | 0.0558 | 0.9039 |
| 6 | | | 25 | | | | | 0.0802 | 0.8849 | 0.0567 | 0.9009 |
| 7 | | | 30 | | | | | 0.0752 | 0.7744 | 0.0562 | 0.9026 |
| 8 | | | | 1 | | | | 0.1117 | 0.4740 | 0.1084 | 0.7760 |
| 9 | | 2 | 5 | 2 | | | | 0.0690 | 0.9153 | 0.0688 | 0.8485 |
| 10 | | | | 5 | 50000 | N-C-D | | 0.0531 | 0.5794 | 0.0633 | 0.8737 |
| 11 | | | | 10 | | | | 0.0746 | 0.6571 | 0.0648 | 0.8668 |
| 12 | | | | 1 | | | | 0.0879 | 0.7907 | 0.0678 | 0.8544 |
| 13 | | 2 | 10 | 2 | | | | 0.0648 | 0.8530 | 0.0669 | 0.8586 |
| 14 | | | | 5 | | | | 0.0755 | 0.8776 | 0.0588 | 0.8923 |
| 15 | | | | 10 | | | | 0.0800 | 0.8457 | 0.0596 | 0.8889 |
| 16 | | | | 1 | | | | 0.0903 | 0.7769 | 0.0677 | 0.8544 |
| 17 | | 2 | 15 | 2 | | | Seigmoid | 0.0612 | 0.8292 | 0.0611 | 0.8822 |
| 18 | 11 | | | 5 | | | | 0.0780 | 0.8329 | 0.0610 | 0.883 |
| 19 | (S1) | | | 10 | | | | 0.0711 | 0.9092 | 0.0577 | 0.8962 |
| 20 | | | | | | D-R | | 0.0580 | 0.9543 | 0.0566 | 0.9166 |
| 21 | | | | | | ExtDBD | | 0.587 | 0.9501 | 0.0521 | 0.9163 |
| 22 | | 1 | 5 | 0 | 50000 | QP | Seigmoid | 0.0613 | 0.9378 | 0.0589 | 0.8935 |
| 23 | | | | | | MP | | 0.0919 | 0.6370 | 0.1169 | 0.8605 |
| 24 | | | | | | D-B-D | | 0.0665 | 0.9298 | 0.0731 | 0.8782 |
| 25 | | | | | | | Linear | 0.1732 | 0.9212 | 0.1463 | 0.9068 |
| 26 | | 1 | 5 | 0 | 50000 | D-R | TanH | 0.1375 | 0.9635 | 0.2291 | 0.7637 |
| 27 | | | | | | | DNNA | 0.0639 | 0.9275 | 0.0697 | 0.8440 |
| 28 | | | | | | | Sine | 0.1290 | 0.9602 | 0.1891 | 0.8505 |
| 29 | | | | | E 5 | | | 0.0523 | 0.9929 | 0.0519 | 0.9166 |
| 30 | | | | | E 10 | | | 0.0620 | 0.8193 | 0.0519 | 0.9166 |
| 31 | | 1 | 5 | 0 | 50000 E 20 | | | 0.0611 | 0.9403 | 0.0519 | 0.9166 |
| 32 | | | | | E 25 | D-R | | 0.0571 | 0.8539 | 0.0519 | 0.9166 |
| 33 | | | | | E 30 | | | 0.0754 | 0.8518 | 0.0519 | 0.9166 |
| 34 | | | | | 52900 | | Seigmoid | 0.0339 | 0.9852 | 0.0517 | 0.9174 |
| 35 | | 1 | 5 | 0 | 65730 | | | 0.0261 | 0.9572 | 0.0517 | 0.9173 |
| 36 | | | | | 67530 | | | 0.0303 | 0.9982 | 0.0518 | 0.9170 |
| 37 | | 1 | 5 | 0 | 50000 | | | 0.0447 | 0.9397 | 0.0696 | 0.8740 |
| 38 | | | | | 55423 | | | 0.0723 | 0.9965 | 0.0689 | 0.8743 |
| 39 | 7 | 1 | 2 | 0 | 50000 | D-R | Seigmoid | 0.0666 | 0.7123 | 0.0706 | 0.8380 |
| 40 | (S2) | | | | 50700 | | | 0.0985 | 0.9941 | 0.0703 | 0.8690 |
| 41 | | 0 | 0 | 0 | 50000 | | | 0.0770 | 0.7066 | 0.0671 | 0.8817 |
| 42 | | | | | 51300 | | | 0.0668 | 0.9905 | 0.0669 | 0.8821 |
| 43 | | | | | 50000 | | | 0.0406 | 0.9427 | 0.0580 | 0.9174 |
| 44 | | | | | 51600 | | | 0.0584 | 0.9745 | 0.0584 | 0.9160 |
| 45 | 7 | 1 | 5 | 0 | 51800 | D-R | Seigmoid | 0.0328 | 0.9607 | 0.0579 | 0.9175 |
| 46 | (S3) | | | | 57300 | | | 0.0197 | 0.9589 | 0.0581 | 0.9171 |
| 47 | | | | | 71400 | | | 0.0985 | 0.9930 | 0.0581 | 0.9171 |
| 48 | | | | | 73800 | | | 0.0559 | 0.9967 | 0.0580 | 0.9174 |
| 49 | | | | | 50000 | | | 0.0637 | 0.5106 | 0.0865 | 0.7934 |
| 50 | | 1 | 5 | 0 | 53376 | | | 0.0383 | 0.9571 | 0.8064 | 0.7938 |
| 51 | 5 | | | | 54000 | D-R | Seigmoid | 0.0899 | 0.9952 | 0.0857 | 0.7982 |
| 52 | (S4) | | | | 56000 | | | 0.0355 | 0.9856 | 0.0867 | 0.7923 |
| 53 | | 1 | 2 | 0 | 52400 | | | 0.0797 | 0.9838 | 0.0888 | 0.7805 |
| 54 | | 0 | 0 | 0 | 52000 | | | 0.0501 | 0.9869 | 0.0835 | 0.8101 |
| 55 | | 1 | 5 | 0 | 51500 | | | 0.0580 | 0.9525 | 0.0768 | 0.8412 |
| 56 | 3 | 1 | 2 | 0 | 50400 | D-R | Seigmoid | 0.0722 | 0.9907 | 0.0804 | 0.8245 |
| 57 | (S5) | 1 | 1 | 0 | 55600 | | | 0.0488 | 0.9506 | 0.0804 | 0.8201 |
| 58 | | 0 | 0 | 0 | 50700 | | | 0.0512 | 0.9670 | 0.0730 | 0.8602 |
| 59 | | 0 | 0 | 0 | 50800 | | | 0.0950 | 0.9191 | 0.0787 | 0.8508 |
| 60 | 1 | 1 | 1 | 0 | 50300 | D-R | Seigmoid | 0.0800 | 0.9349 | 0.0861 | 0.7983 |
| 61 | (S6) | 1 | 2 | 0 | 53300 | | | 0.0635 | 0.9320 | 0.0832 | 0.8175 |
| 62 | | 2 | 1 | 1 | 52100 | | | 0.0758 | 0.8892 | 0.0923 | 0.7600 |

Table 6.16: Selection of the best ANN mark up model

| Model No. | No. of Inputs | Training | | Testing | | Performance Index (PI) |
|---|---|---|---|---|---|---|
| | | RMS | $R^2$ | RMS | $R^2$ | |
| 1 | 11 | 0.0566 | 0.8413 | 0.0538 | 0.9113 | 0.8211 |
| 2 | | 0.0592 | 0.9436 | 0.0571 | 0.8989 | 0.8631 |
| 3 | | 0.0659 | 0.6648 | 0.0579 | 0.8962 | 0.7186 |
| 4 | | 0.0630 | 0.7442 | 0.0569 | 0.9005 | 0.7624 |
| 5 | | 0.0586 | 0.7951 | 0.0558 | 0.9039 | 0.7923 |
| 6 | | 0.0802 | 0.8849 | 0.0567 | 0.9009 | 0.8245 |
| 7 | | 0.0752 | 0.7744 | 0.0562 | 0.9026 | 0.7728 |
| 8 | | 0.1117 | 0.4740 | 0.1084 | 0.7760 | 0.5150 |
| 9 | | 0.0690 | 0.9153 | 0.0688 | 0.8485 | 0.8130 |
| 10 | | 0.0531 | 0.5794 | 0.0633 | 0.8737 | 0.6684 |
| 11 | | 0.0746 | 0.6571 | 0.0648 | 0.8668 | 0.6923 |
| 12 | | 0.0879 | 0.7907 | 0.0678 | 0.8544 | 0.7447 |
| 13 | | 0.0648 | 0.8530 | 0.0669 | 0.8586 | 0.7900 |
| 14 | | 0.0755 | 0.8776 | 0.0588 | 0.8923 | 0.8178 |
| 15 | | 0.0800 | 0.8457 | 0.0596 | 0.8889 | 0.7975 |
| 16 | | 0.0903 | 0.7769 | 0.0677 | 0.8544 | 0.7367 |
| 17 | | 0.0612 | 0.8292 | 0.0611 | 0.8822 | 0.7946 |
| 18 | | 0.0780 | 0.8329 | 0.0610 | 0.8830 | 0.7885 |
| 19 | | 0.0711 | 0.9092 | 0.0577 | 0.8962 | 0.8383 |
| 20 | | 0.0580 | 0.9543 | 0.0566 | 0.9166 | 0.8782 |
| 21 | | 0.5870 | 0.9501 | 0.0521 | 0.9163 | 0.6137 |
| 22 | | 0.0613 | 0.9378 | 0.0589 | 0.8935 | 0.8556 |
| 23 | | 0.0919 | 0.6370 | 0.1169 | 0.8605 | 0.6444 |
| 24 | | 0.0665 | 0.9298 | 0.0731 | 0.8782 | 0.8342 |
| 25 | | 0.1732 | 0.9212 | 0.1463 | 0.9068 | 0.7543 |
| 26 | | 0.1375 | 0.9635 | 0.2291 | 0.7637 | 0.6803 |
| 27 | | 0.0639 | 0.9275 | 0.0697 | 0.8440 | 0.8190 |
| 28 | | 0.1290 | 0.9602 | 0.1891 | 0.8505 | 0.7463 |
| 29 | | 0.0523 | 0.9929 | 0.0519 | 0.9166 | 0.9027 |
| 30 | | 0.0620 | 0.8193 | 0.0519 | 0.9166 | 0.8110 |
| 31 | | 0.0611 | 0.9403 | 0.0519 | 0.9166 | 0.8720 |
| 32 | | 0.0571 | 0.8539 | 0.0519 | 0.9166 | 0.8308 |
| 33 | | 0.0754 | 0.8518 | 0.0519 | 0.9166 | 0.8206 |
| 34 | | 0.0339 | 0.9852 | 0.0517 | 0.9174 | 0.9085 |
| 35 | | 0.0261 | 0.9572 | 0.0517 | 0.9173 | 0.8984 |
| **36** | | **0.0303** | **0.9982** | **0.0518** | **0.9170** | **0.9166** |
| 37 | 7 | 0.0447 | 0.9397 | 0.0696 | 0.8740 | 0.8497 |
| **38** | | **0.0723** | **0.9965** | **0.0689** | **0.8743** | **0.8648** |
| 39 | | 0.0666 | 0.7123 | 0.0706 | 0.8380 | 0.7066 |
| 40 | | 0.0985 | 0.9941 | 0.0703 | 0.8690 | 0.8472 |
| 41 | | 0.0770 | 0.7066 | 0.0671 | 0.8817 | 0.7221 |
| 42 | | 0.0668 | 0.9905 | 0.0669 | 0.8821 | 0.8695 |
| 43 | 7 | 0.0406 | 0.9427 | 0.0580 | 0.9174 | 0.8808 |
| 44 | | 0.0584 | 0.9745 | 0.0584 | 0.9160 | 0.8869 |
| 45 | | 0.0328 | 0.9607 | 0.0579 | 0.9175 | 0.8938 |
| 46 | | 0.0197 | 0.9589 | 0.0581 | 0.9171 | 0.8991 |
| 47 | | 0.0985 | 0.9930 | 0.0581 | 0.9171 | 0.8768 |
| **48** | | **0.0559** | **0.9967** | **0.0580** | **0.9174** | **0.9001** |
| 49 | 5 | 0.0637 | 0.5106 | 0.0865 | 0.7934 | 0.5769 |
| 50 | | 0.0383 | 0.9571 | 0.8064 | 0.7938 | 0.4531 |
| 51 | | 0.0899 | 0.9952 | 0.0857 | 0.7982 | 0.8089 |
| **52** | | **0.0355** | **0.9856** | **0.0867** | **0.7923** | **0.8279** |
| 53 | | 0.0797 | 0.9838 | 0.0888 | 0.7805 | 0.7979 |
| 54 | | 0.0501 | 0.9869 | 0.8350 | 0.8101 | 0.4560 |
| 55 | 3 | 0.058 | 0.9525 | 0.0768 | 0.8412 | 0.8295 |
| 56 | | 0.0722 | 0.9907 | 0.0804 | 0.8245 | 0.8313 |
| 57 | | 0.0488 | 0.9506 | 0.0804 | 0.8201 | 0.8208 |
| **58** | | **0.0512** | **0.9670** | **0.0730** | **0.8602** | **0.8515** |
| 59 | 1 | 0.0950 | 0.9191 | 0.0787 | 0.8508 | 0.7981 |
| 60 | | 0.0800 | 0.9349 | 0.0861 | 0.7983 | 0.7836 |
| **61** | | **0.0635** | **0.9320** | **0.0832** | **0.8175** | **0.8014** |
| 62 | | 0.0758 | 0.8892 | 0.0923 | 0.7600 | 0.7406 |

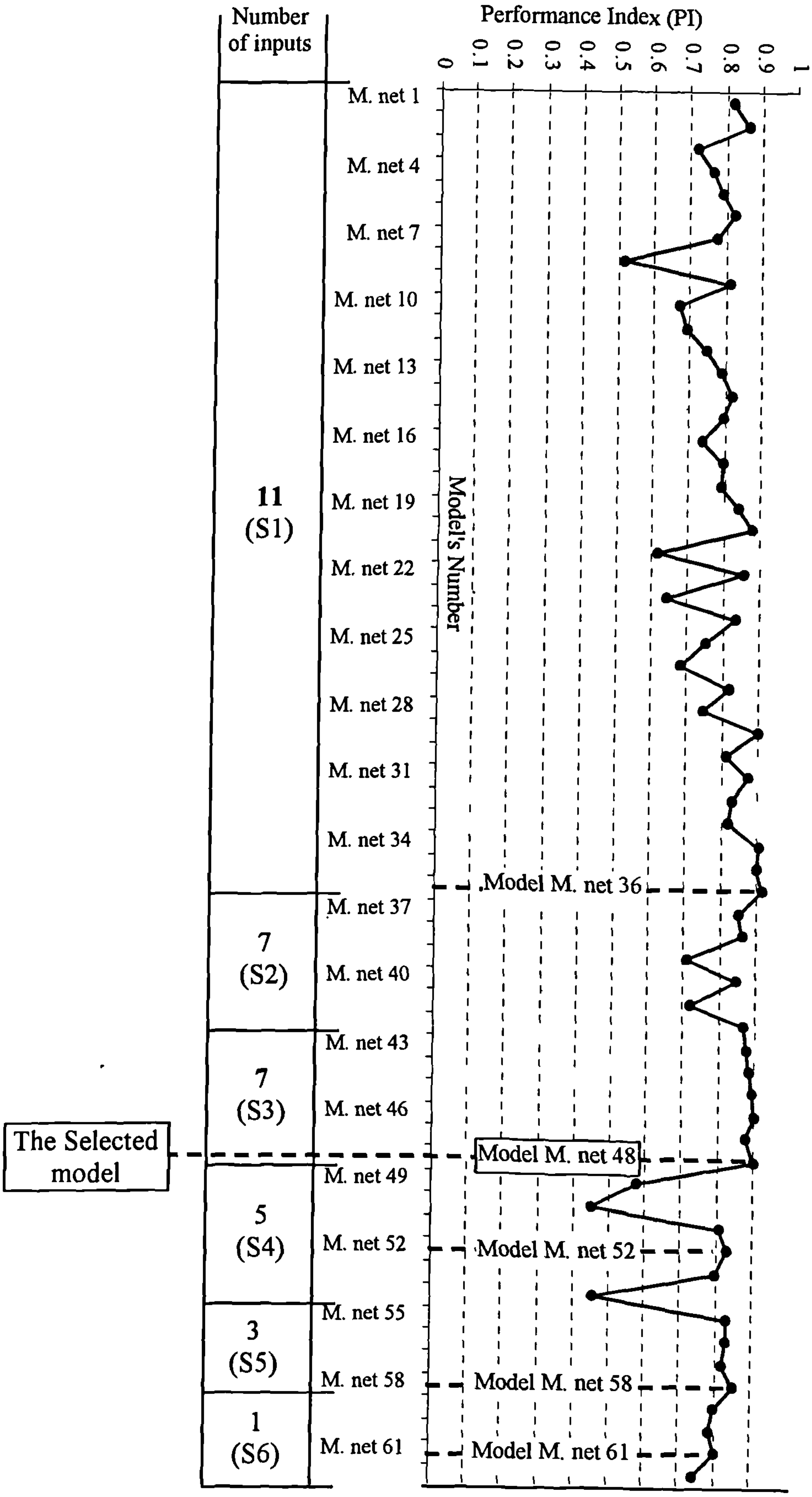



Fig. 6.26: Selection of the best ANN mark up model

- Selecting the best model developed for each of the considered sets of inputs, i.e. S1 to S6, considering only the PI criterion; and,
- From the six models selected in the first step, the optimum model is selected taking into account both of the performance index (PI) and the number of inputs of each one.

Table 6.17 shows the models selected in the first step along with their performance indices and number of inputs. The model, which has as few inputs variable as possible should be selected without compromising the performance considerably.

Table 6.17: Selection of the final ANN mark up model

| | | Model 36 | Model 38 | Model 48 | Model 52 | Model 58 | Model 61 |
|---|---|---|---|---|---|---|---|
| Inputs | No. | **11** | 7 | 7 | 5 | 3 | 1 |
| | Set | S1 | S2 | S3 | S4 | S5 | S6 |
| PI | | **0.9166** | 0.8648 | **0.9001** | 0.8279 | 0.8515 | 0.8014 |

Thus, model 48 was considered as the best model because it corresponds to the best combination of high performance and fewer inputs. The next section describes the structure of the selected model (M net 48).

### 6.5.7 The Selected ANN Mark up Model

This section illustrates the topology of the selected ANN mark up model (M. net 48) and provides all the parameters used in scaling/de-scaling the inputs and outputs, training parameters, and the final connection weights. Model M. net 48 is composed of the following layers:

1. Input layer (*I*) containing seven nodes for the seven mark up variables contained in S3 (column 5 of Table 6.13) and a bias node (f0). The input nodes are fully connected to the next layer. The bias node is connected to all the subsequent layers;
2. Hidden layer (*J*) containing five processing elements with Sigmoid transfer function. All these PEs are fully connected to the output layer; and,

3. Output layer (*O*) containing one output PE with Sigmoid transfer function.

The architecture of this model is illustrated in Fig. 6.27.

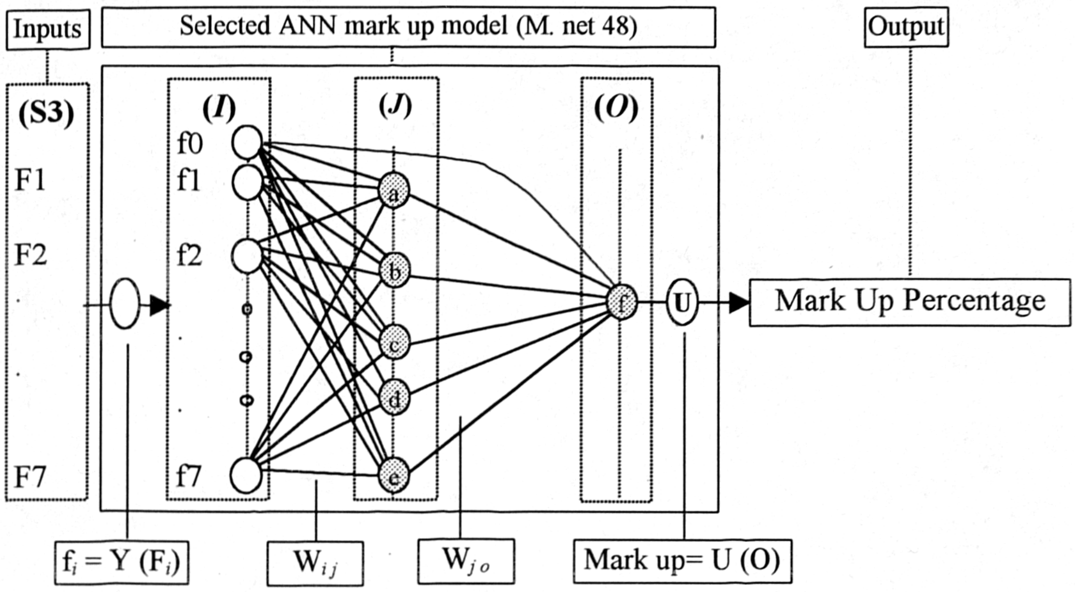



Fig. 6.27: Structure of the ANN mark up model

The final connection weights, which store the knowledge elicited from the training sample were extracted manually from the trained M. net 48 model and presented in Table 6.18, where (a, b, c, d, e, and f) are the hidden and output processing elements of the selected ANN mark up model and (f0, f1, ..., and f7) are the input nodes of this model.

Table 6.18: Connection weights between the processing elements of M. net 48

| | | a | b | c | d | e |
|---|---|---|---|---|---|---|
| | f1 | -0.457086 | 0.627934 | 0.638201 | -0.308204 | -0.16772 |
| | f2 | 0.045218 | -0.532546 | -0.473573 | 0.212508 | 0.142174 |
| | f3 | 0.249744 | 0.136118 | -0.046584 | 0.905798 | 0.733477 |
| | f4 | 0.200338 | -0.373398 | -0.241843 | 0.076553 | 0.395644 |
| | f5 | -0.085782 | -0.536525 | -0.549711 | -0.183671 | 0.220918 |
| | f6 | -0.218108 | 0.149007 | 0.261252 | -0.263731 | 0.047523 |
| | f7 | 0.447643 | 0.109775 | -0.215258 | 0.044919 | 0.189513 |
| | f0 = +1 | 0.028889 | -0.52983 | -0.898866 | -0.134398 | -0.21530 |
| f | -0.12269 | -0.337893 | 0.815870 | 1.210634 | -0.497904 | -0.89312 |

Table 6.19 shows the "MinMax Table" generated automatically from the training file (Appendix D). The selected target network ranges are shown in Table 6.20.

Table 6.19: The "MinMax Table" used in model M. net 48

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | Output |
|---|---|---|---|---|---|---|---|---|
| Min | 0 | 0 | 3 | 3 | 1 | 2 | 2 | 0.09 |
| Max | 5 | 5 | 6 | 6 | 5 | 6 | 6 | 0.2 |

Table 6.20: Target network ranges used in model M. net 48

| | Input | Output |
|---|---|---|
| Minimum | -1.00 | 0.200 |
| Maximum | +1.00 | 0.800 |

Equation D.1/Appendix D was used to produce the linear scaling functions based on the values of the "MinMax Table" and the network target ranges. These functions are shown in Table 6.21 along the corresponding input factors.

Table 6.21: Scaling the input real-world values to the desired values

| No. | Factor Name | Desired (Scaled) values ($f_i$) | Equation No. |
|---|---|---|---|
| F1 | Risks expected | f1= 0.4*F1-1 | (6.21) |
| F2 | Availability of owned equipment | f2= 0.4*F1 -1 | (6.22) |
| F3 | Confidence in the cost estimate | f3= 0.666667*F3-3 | (6.23) |
| F4 | Competence of the expected competitors | f4= 0.666667*F4-3 | (6.24) |
| F5 | Proportions that can be constructed mechanically | f5= 0.5*F5-1.5 | (6.25) |
| F6 | Rigidity of specifications | f6= 0.5*F6-2 | (6.26) |
| F7 | Site accessability | f7= 0.5*F7-2 | (6.27) |

The linear function used by the model to de-scale the initial output values to real world values is as follows (see Equation D.3/Appendix D):

Final output = 0.183333 * scaled output ($O$) + 0.053333 (6.28)

The following section studies the stability of the developed ANN mark up model and the effect of the input variables on its behaviour.

### 6.5.7.1 Sensitivity Analysis

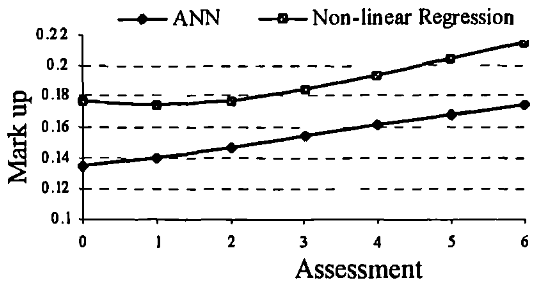
Lack of stability is the main limitation of the non-linear regression mark up model developed in the previous Chapter. Whereas, unrealistic recommendations can be made if certain factors were assigned extreme scores and small variations in certain factors may cause large variation in the model output (see section 5.4.5). In section 5.7, the ANN technique was suggested as a potential solution for the lack of stability problem that undermines the reliability of the non-linear regression model. The question to be answered in this section is: "is the developed ANN mark up model stable?". To answer this question, the sensitivity of the model output to variations in its inputs was examined. The outputs of the model were recorded while changing the assessment of the first factor (F1). Meanwhile, the other factors were set to the mid-point scenario (3 score). The same process was repeated for all the other factors. Table 6.22 shows the outputs computed for different assessments given to each input factor while setting the other factors to the mid-point score.

Table 6.22: Sensitivity of the model output to variation in the inputs.

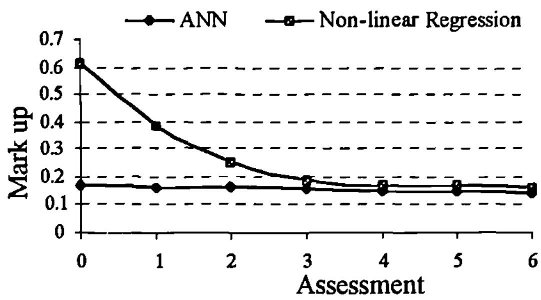
| Factors | Assessments | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | (3) | 4 | 5 | 6 |
| F1 | 0.1340 | 0.1401 | 0.1467 | 0.1536 | 0.1608 | 0.1678 | 0.1745 |
| F2 | 0.1690 | 0.1640 | 0.1588 | 0.1536 | 0.1486 | 0.1438 | 0.1393 |
| F3 | 0.1650 | 0.1626 | 0.1589 | 0.1536 | 0.1466 | 0.1384 | 0.1301 |
| F4 | 0.1725 | 0.1666 | 0.1603 | 0.1536 | 0.1468 | 0.1400 | 0.1333 |
| F5 | 0.1718 | 0.1659 | 0.1598 | 0.1536 | 0.1477 | 0.1423 | 0.1375 |
| F6 | 0.1444 | 0.1475 | 0.1505 | 0.1536 | 0.1567 | 0.1598 | 0.1628 |
| F7 | 0.1566 | 0.1557 | 0.1547 | 0.1536 | 0.1525 | 0.1514 | 0.1503 |

Figures 6.28a to 6.28g compare between the sensitivity of the ANN model to changes in its inputs and the sensitivity of the non-linear regression model to changes in the same variables (see Table 6.13). These figures show that:

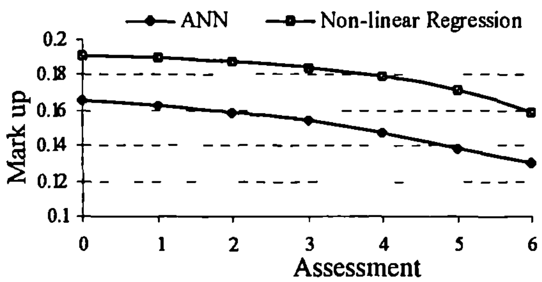
1. Extreme values of any input variable does not cause the ANN model to produce unrealistic mark up recommendations;
2. Small changes in any input variable does not cause large changes, i.e. steps, in the output of this model; and,
3. The regression model will produce unexpected mark up recommendations for extreme values of the following variables:
   - Availability of owned equipment (see Fig. 6.28b);
   - Proportions that can be constructed mechanically (see Fig. 6.28e);
   - Rigidity of specifications (see Fig. 6.28f); and,
   - Site accessability (see Fig. 6.28g).



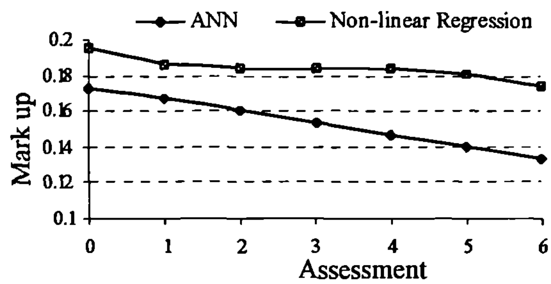

a: Influence of the "Risks expected"



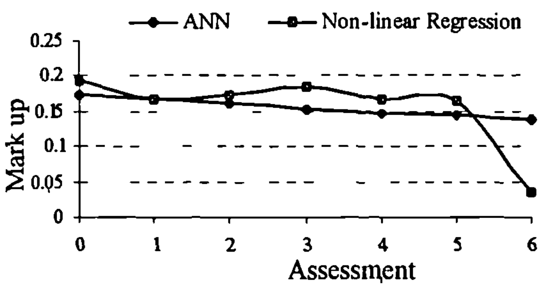

b: Influence of the "Availability of owned equipment"



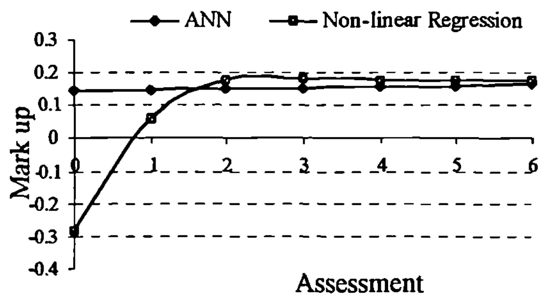

c: Influence of the "Confidence in the cost estimate"



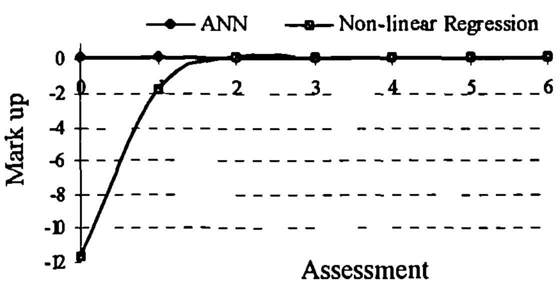

d: Influence of the "Competence of the expected competitors"




e: Influence of the "Proportions that can be constructed mechanically"




f: Influence of the "Rigidity of specifications"




g: Influence of the "Site accessability"

Fig. 6.28: Sensitivity of the ANN and the non-linear regression mark up models to changes in individual input factors

Thus, it can be concluded that the ANN mark up model provided a successful solution for the lack of stability, which undermines the reliability of the regression model. However, the ANN mark up model needs to be tested against real life bidding situations before stating that it is superior to the non-linear regression model. This is explained in the following section.

### 6.5.7.2 Testing and Validation

The contractor's assessments of the validation samples were presented to the ANN mark up model, which produced a mark up percentage for each bidding situation. Table 6.23 shows the model recommendation with the actual mark up, error, absolute error, and percentage error for each one of the test cases. The mean error of the model recommendations was very small (ME = 0.003) and the root mean square error was only (RMS = 0.0122) indicating high reliability of the developed model. Another measure, which gives the same indication is the high correlation between the actual and predicted mark ups (R = 0.897).

Table 6.23: Actual and predicted mark ups of fifteen real life bidding situations

| Project Number | Actual Mark up | ANN mark Up Recommendations | Error | | |
|---|---|---|---|---|---|
| | | | Value | Absolute | (%) |
| 1 | 0.12 | 0.125 | -0.005 | 0.005 | 4.406 |
| 2 | 0.14 | 0.126 | 0.014 | 0.014 | 9.678 |
| 3 | 0.15 | 0.133 | 0.017 | 0.017 | 11.536 |
| 4 | 0.13 | 0.154 | -0.024 | 0.024 | 18.715 |
| 5 | 0.18 | 0.169 | 0.011 | 0.011 | 6.145 |
| 6 | 0.15 | 0.133 | 0.017 | 0.017 | 11.063 |
| 7 | 0.18 | 0.175 | 0.005 | 0.005 | 2.861 |
| 8 | 0.16 | 0.143 | 0.017 | 0.017 | 10.539 |
| 9 | 0.12 | 0.113 | 0.007 | 0.007 | 5.495 |
| 10 | 0.11 | 0.114 | -0.004 | 0.004 | 4.070 |
| 11 | 0.10 | 0.099 | 0.001 | 0.001 | 0.931 |
| 12 | 0.09 | 0.106 | -0.016 | 0.016 | 17.538 |
| 13 | 0.13 | 0.122 | 0.008 | 0.008 | 5.862 |
| 14 | 0.15 | 0.143 | 0.007 | 0.007 | 4.937 |
| 15 | 0.11 | 0.115 | -0.005 | 0.005 | 4.696 |
| Average | | | 0.003 | 0.011 | 7.900 |
| RMS | | | 0.0122 | | |

The mean percentage error was 7.9% as shown in Table 6.21. Therefore, it can be concluded that the developed model is (92.1%) accurate in simulating the actual mark ups set by contractors in real life for the validation projects.
After finalising the ANN "bid/no bid" and mark up models, these two models can be combined together to develop an integrated ANN bidding strategy model as explained in the following section.

### 6.6 An Integrated ANN Bidding Strategy Model

The ANN "bid/no bid" and "mark up models developed in the previous sections were combined to form an integrated bidding model to help contractors in dealing systematically with new bidding situations. All a contractor needs is to provide his/her subjective assessment of the considered bidding situation in terms of twelve "bid/no bid" criteria (set S2 in Table 6.2). Then, the model provides a "bid/no bid" recommendation with a certain degree of confidence. Before accepting or rejecting this recommendation, a "what-if" analysis can be performed. This could help the contractor to be more confident in his final decision. If a "bid" decision was made, the contractor can assess the considered bidding situation in terms of another five factors (set S3 in Table 6.13). Two of the mark up factors are shared with the "bid/no bid" decision (confidence in the cost estimate" and "proportions that can be constructed mechanically). Upon these assessments, the ANN mark up model can provide a mark up recommendation. Also, a what-if analysis can be made before fixing the mark up size.

### 6.7 Summary and Discussion

Through a formal questionnaire survey, the important factors that affect the bidding decisions in Syria were identified. The most important factors were selected and considered in collecting data on real life bidding situations. Based on a simple correlation analysis, different sets of potential input variables were identified. A systematic trial and error procedure was implemented to develop numerous neural network models for both bid/no bid and mark up decisions. The best model was selected for each decision. The final "bid/no bid" model is composed of one input layer (buffer) with twelve nodes, two hidden layers (five nodes, i.e. processing elements, in the first one and one node in the second), and one output layer with one node for the only output (neural bidding index). This index is used by a simple confidence model to produce a "bid/no bid" recommendation with a certain degree of confidence. Testing the final neural network "bid/no bid" model revealed that the model has a highly satisfactory predictive accuracy. The model simulated the actual decisions of 90% of the testing cases while the parametric model simulated only 85% of them. This certifies that the ANN technique is a viable tool for modelling the "bid/no bid" process. Also, the developed neural network mark up model outperformed the regression model developed in the previous chapter. The mark up recommendations produced by this model for the testing cases are closer than the recommendations produced by the regression model to the actual ones ($ME_{ann}$ = 0.002, $ME_{reg}$ = 0.005). The network parameters (i.e., weights, learning rules, transfer functions, topology, etc.) reveal nothing that can rationally be interpreted as a causal explanation of the real world relationship modelled by the trained network. This opacity problem has two effects on ANN technology (Boussabaine et al. 1999). Firstly, it reduces confidence in ANN technology. Secondly, it makes the design of ANN systems ad-hoc based. The following chapter explains an attempt to overcome the opacity problem of the neural network bidding models by applying the neurofuzzy technology. Combining neural networks with fuzzy logic models helps to explain their behaviour and to validate their performance.

# CHAPTER 7
# A NEUROFUZZY EXPERT SYSTEM FOR COMPETITIVE TENDERING

## 7.1 Introduction

Uncertainty and fuzziness in information related to a new construction project, the client, the potential competitors, and the overall construction market make it a very complex process to decide whether to bid or not to bid and how much to mark up the estimated project cost to produce the final bid price. Usually, these decisions are derived from intuition and subjective judgement based on past experience in a subconscious way (Ahmad, 1988a, 1988b). Even experienced contractors might not be able to explain how they make these decisions. These properties call for hybrid decision-support systems that can learn from real examples and take into account the uncertain and fuzzy nature of the bidding problem. Combining the neural networks systems with fuzzy logic models could be the optimum answer to this problem as suggested in section 6.7. Fuzzy and neural network hybrid decision support systems are able to mimic the ability of the human mind to effectively employ modes of reasoning that are approximate rather than exact (Zadeh, 1994). General reviews of the ANN and fuzzy logic techniques were provided in Chapter 2. The following sections are devoted to explain the methodology adopted to develop, optimise, and validate a NeuroFuzzy bidding model. The Neurofuzzy module of a fuzzy logic development software called "*Fuzzy* TECH 5.10b for Business Professional" was employed in this study.

## 7.2 Development of a Neurofuzzy "Bid/No Bid" Model

The development of neurofuzzy models involves a sereis of interactive processess. Fig. 7.1 shows the sequence used in the development of the neurofuzzy bidding model.

The developement of such model requires one or more of the following types of data:

- Rules of thumb, the collection of which is highly difficult;

- Typical data, which are rarely available for developing a new model; and,
- Raw data, which have to be processed prior to implementation. Also, it is useful to cluster these data to reduce the inherent noise.

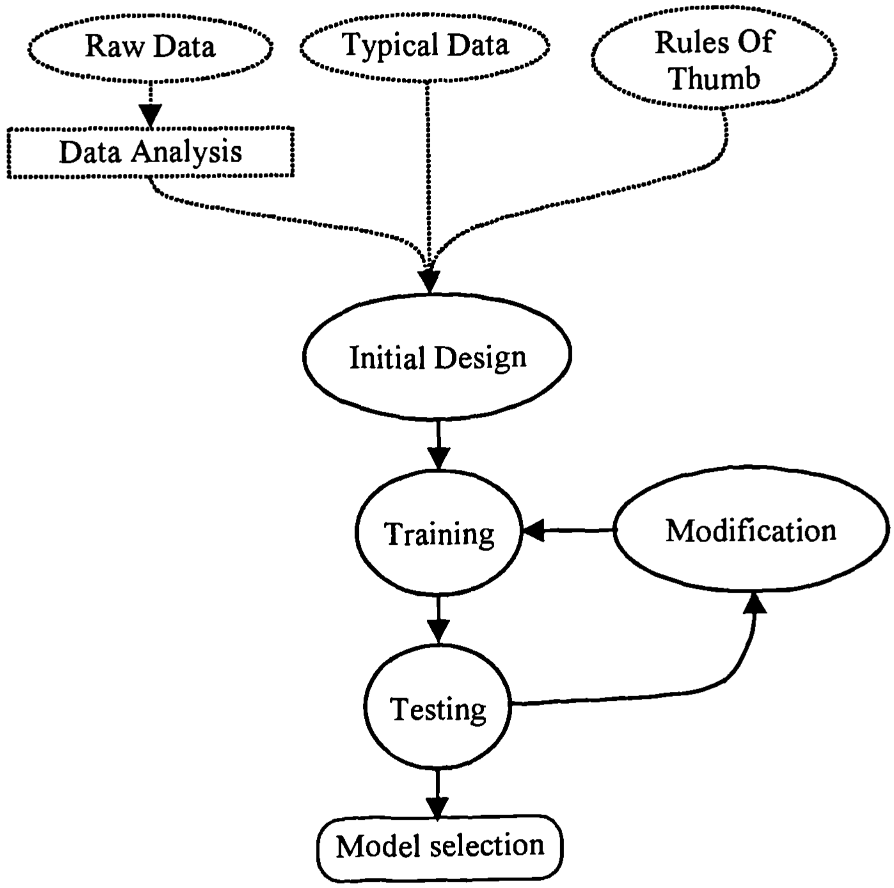



Fig. 7.1: Framework of the development process

### 7.2.1 Initial Design

In this step, an empty fuzzy logic system is developed and made ready for training. Fig. 7.2 shows the main components of a fuzzy logic system. Developing such system involves the following tasks:

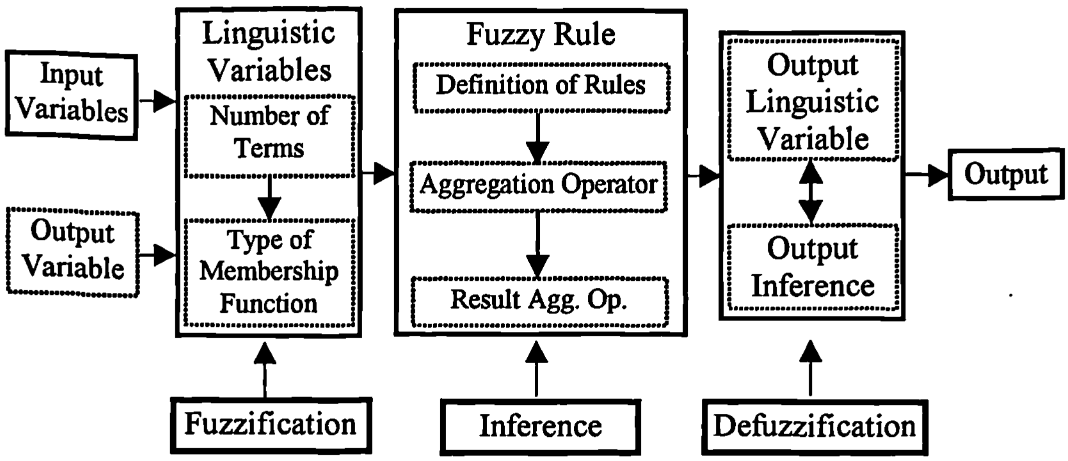



Fig. 7.2: The general structure of a fuzzy logic system

1. Definition of input and output variables. The same input variables of the final ANN "bid/no bid" model developed in chapter 6 (set S2 in Table 6.2) were considered in developing the fuzzy logic "bid/no bid" system. This was justified by:

- These input variables are the most influential "bid/no bid" criteria;
- There is no need to consider additional variables as suggested by the high accuracy of the ANN model; and,
- This will enable more realistic comparison between ANN and neurofuzzy techniques.

One output is expected from the neurofuzzy model. This output is called the neurofuzzy bidding index (NFBI). The closer NFBI to one, the more confidence in the "bid" recommendation and the closer it is to zero, the more confidence in the "no bid" recommendation.

2. Setting the linguistic variables for the considered inputs and output. The main decisions to be made in this stage are:

- Number of linguistic terms for each variable. As a start, the number of terms in all input variables was set to three and the number of terms in the output variable was set to five (see section 2.8.1.1);
- Types of membership functions. For all input variables, the cubic interpolative S-shaped MBFs was used because it provides more accurate models of human concepts for complex decision-support applications. For the output variable, the Λ-type ,i.e. linear (L), was used because most applications use this type of MBFs

for output variables (Altrock, 1997). All the selected membership functions are standard, i.e. maximum is always ($\eta$=1) and minimum is ($\eta$=0).

Fig. 7.3 shows the " Accessability" linguistic variable as a example of the input variables. The output linguistic variable is shown in Fig. 7.4.

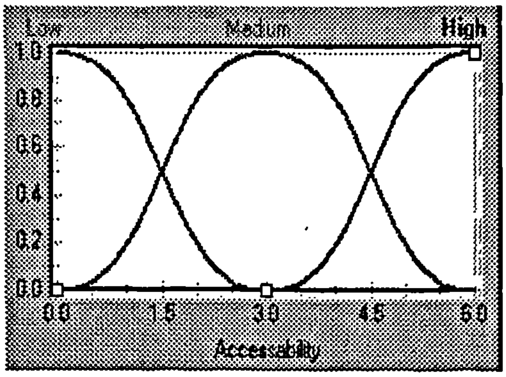



Fig. 7.3: The "accessability" input linguistic variable

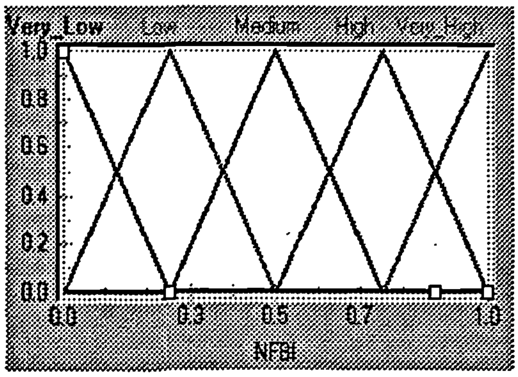



Fig. 7.4: Linguistic variable for the output variable "NFBI"

3. Setting the inference rule base. This involves the following tasks:

- Definition of the fuzzy rules: The collection of these rules from the domain experts is a highly difficult process. Therefore, the neurofuzzy module of the *fuzzy*TECH development software was used to generate the fuzzy rule base from real examples. The rule base has to be arranged in one or more rule block. The maximum number of inputs that can be included in a rule block is eight variables. The following equation produces the total number of all potential rules that cover all the possible combinations between the considered inputs and outputs in a rule block:

$$N = NT_{Input\,(1)} * \ldots * NT_{Input\,(i)} * \ldots * NT_{Input\,(n)} * NT_{Output\,(1)} * \ldots . * NT_{Output\,(j)} * \ldots . * NT_{Output\,(m)} \qquad (7.1)$$

Where:

N is number of all potential rules;

$NT_{Input\,(i)}$ is the number of terms of the input variable (*i*) included in the considered rule block;

n is the number of inputs included in the considered rule block;

$NT_{Output\,(j)}$ is the number of terms of the output variable (*j*); and,

m is the number of outputs included in the considered rule block.

The maximum rules in a rule block is 1024. These constraints control the number of rule blocks required. In the current case, there are twelve inputs, each of which has three terms and one output with five terms. The one-block option is not possible as the maximum inputs allowed are eight. Considering two rule block each with six inputs and the same output will result in 3645 rules (from equation 7.1) in each block. Therefore, three blocks each with 405 rules were considered. These rules were automatically generated by the software used. The Degrees of Support (DS) of the generated rules were set to zero. DSs will be modified during the training phase.

- Selection of the aggregation operators (see section 2.8.1.2). The "MinMax" premise aggregation operator with no compensation parameter and the "Max" result aggregation operator were adopted. These will be optimised later in the modification phase as explained in section 7.2.4.

4. Selection of the output inference method, i.e. defuzzification method. The Centre of Maximum (CoM) was used in this stage.

The resultant model was called the initial model (model 1). The main characteristics of this model (with all the subsequent models examined during the optimisation process) are shown in Table 7.1. The general structure of model 1, which determines the information flow from the input space to the output space through the rule blocks, is illustrated in Fig. 7. 5.

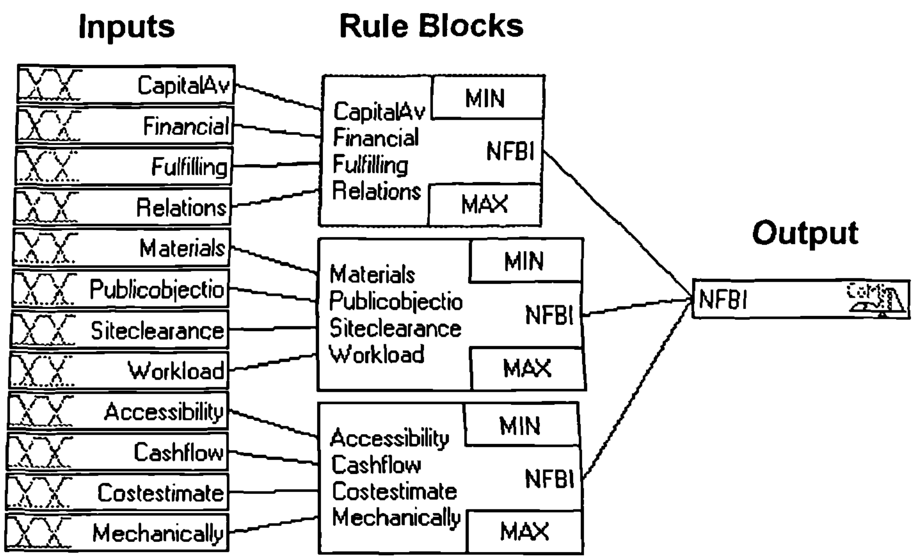



Fig. 7.5: The general structure of model 1

The input values are fuzzified and translated into linguistic expressions such as "Low", "Medium", or "High". Fuzzy inference takes place in the rule blocks, which contain the linguistic control rules. In the output interface, the linguistic bidding index (Very Low, Low, Medium, High, Very High) is defuzzified and translated back into a numerical value. Model 1 is completely ignorant at this stage because the degrees of support, of all its rules are zeros. The following section explains how these DSs are modified by training Model 1 using real life bidding examples.

### 7.2.2 Training

Once the empty fuzzy logic system is generated, it can be trained using the training data that are in the required format. Rules and membership functions of the inputs and the output variables can be modified by training. In this model, only the rules, i.e. degrees of support, were trained. The training process can be ceased manually or by setting a cut-off point where the training process is stopped automatically when the average error is equal to the selected cut-off point.

Fig. 7.6 shows the performance of Model 1 before training. Fig. 7.7 shows the model performance after a fixed number of learning iterations (5 iterations) using one hundred and sixty two real life bidding situations, which have been also used in training the ANN bidding models. The average deviation between the actual output values of the training examples and the predicted values for these examples is produced automatically by *fuzzy*TECH. The generated average deviation is a measurement parameter of the training performance of Model 1 after 5 iterations. The training process adjusts the degrees of support. Important rules will have high degrees of support, i.e. close to one. Unimportant rules will have low DSs, i.e. close to zero. These rules can be deleted, as they do not have significant influence on the model's behaviour. Fig.7.7 shows that Model 1 is able to map the input space of the training samples to the output space with an average error 22.55% after 5 iterations. This parameter is recorded in Table 7.1. Many other models with different characteristics will be trained for the same number of iterations to enable a fair comparison between different development parameters as explained in section 7.2.4

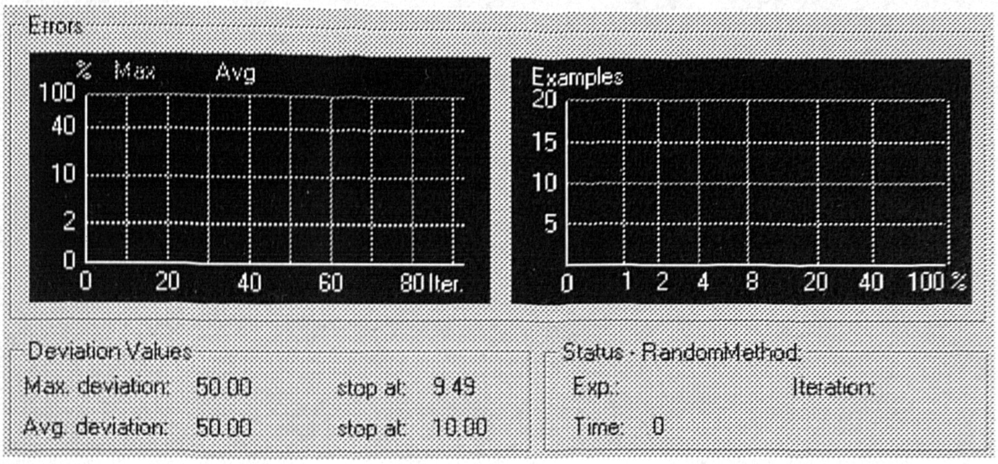



Fig. 7.6: Model 1 before training

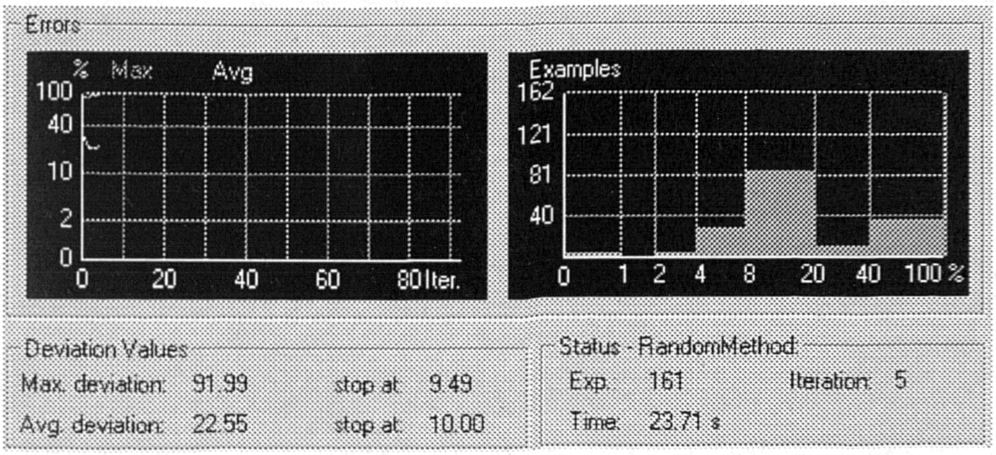



Fig. 7.7: Model 1 after training

### 7.2.3 Testing

After completing five training iterations, model 1 has been tested using another twenty real life bidding situations reserved for the testing process. The average testing error produced by model 1 is (Ave. $Dev._{testing}$ = 27.55%). This parameter is recorded in Table 7.1. The average deviations of training and testing are used to judge the performance of model 1 and to compare it to others.

### 7.2.4 Modification

The previous sections explained how Model 1 was designed, trained and tested. The current section explains a systematic procedure adopted to produce the best possible neurofuzzy "bid/no bid" model. This process involves the following actions:

1. Revision of the aggregation operators/parameters;
2. Revision of the linguistic variables, i.e. terms, membership functions;
3. Revision/extension of the rule base;
4. Revision of the output inference, i.e. defuzzification method; and,
5. More learning iterations

The Ave. $Dev._{training}$ and Ave. $Dev._{testing}$ parameters were recorded in Table 7.1 for all the examined models during the modification process. Fig. 7.8 illustrates the sequence of the optimisation activities used in this work. It can be explained as follows:

1. Selecting the "Min-Max" aggregation operator and trying different compensation parameters (0.1, 0.15, and 0.20) for models 2 to 4. Fig. 7.9 shows that the MinMax operator performs better in the current case without any compensation (see section 2.8.1.2.1 for more details about the aggregation operators and the compensation parameter).

2. Next, the "Min-Ave" operator was selected and different compensation parameters were experimented with (models 5 to 8 in Table 7.1). Again, no compensation is required for the Minimum-Average (Min-Ave). operator as shown in Fig. 7.10.

3. Then, the " $\gamma$ " aggregation operator was used and different parameters were examined (models 9 to 12 in Table 7.1). This operator performs better with (0.10) compensation parameter as shown in Fig. 7.11.

4. Comparing the best cases of all the aggregation operators showed that the " $\gamma$" operator with (0.10) compensation parameter (Model 10) is more appropriate as illustrated in Fig. 7.12.

Table 7.1: Selection of the best structure of the neurofuzzy bid/no bid model

| Model | Inputs | | | Rule Blocks | | | | Outputs | | | | Learning | | Testing | Performance Index (PI) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No. | Terms No. | Terms Shape | No. | Premise Aggregation Type | Premise Aggregation Parameter | Result Aggregation | No. | Terms No. | Terms Shape | Output Inference | Av. Dev. | Iterations | Av. Dev. | |
| 1 | 12 | 3 | S | 3 | Min/ Max | 0.00 | Max | 1 | 5 | L | CoM | 22.55 | 5 | 27.39 | 75.03 |
| 2 | | | | | | 0.10 | | | | | | 26.10 | | 27.10 | 73.40 |
| 3 | | | | | | 0.15 | | | | | | 27.53 | | 31.85 | 70.31 |
| 4 | | | | | | 0.20 | | | | | | 28.64 | | 32.09 | 69.64 |
| 5 | 12 | 3 | | 3 | Min/ Avg | 0.00 | | | | | | 21.88 | | 25.05 | 76.54 |
| 6 | | | | | | 0.10 | | | | | | 24.97 | | 25.63 | 74.70 |
| 7 | | | | | | 0.15 | | | | | | 23.90 | | 25.36 | 75.37 |
| 8 | | | | | | 0.20 | | | | | | 32.54 | | 32.23 | 67.62 |
| 9 | 12 | 3 | | 3 | $\gamma$ | 0.00 | | | | | | 18.63 | | 21.58 | 79.90 |
| 10 | | | | | | 0.10 | | | | | | 16.10 | | 21.22 | 81.34 |
| 11 | | | | | | 0.15 | | | | | | 21.48 | | 20.23 | 79.15 |
| 12 | | | | | | 0.20 | | | | | | 22.07 | | 22.45 | 77.74 |
| 13 | 12 | 5 | | 4 | $\gamma$ | 0.10 | Max | | | | | 9.65 | | 17.11 | 86.62 |
| 14 | 12 | 7 | | 6 | $\gamma$ | 0.10 | Max | | | | | 11.02 | | 22.49 | 83.25 |
| 15 | 12 | 5 | | 4 | $\gamma$ | 0.10 | B-SUM | | | | | 8.70 | | 16.07 | 87.62 |
| 16 | 12 | 5 | S | 4 | $\gamma$ | 0.10 | B-SUM | 1 | 5 | L | MoM | 7.41 | 5 | 7.50 | 92.55 |
| 17 | 12 | 5 | S | 4 | $\gamma$ | 0.10 | B-SUM | 1 | 5 | L | Fast CoA | 15.42 | 5 | 19.28 | 82.65 |
| 18 | 12 | 5 | S | 4 | $\gamma$ | 0.10 | B-SUM | 1 | 7 | L | CoM | 14.81 | 5 | 22.50 | 81.35 |
| 19 | 12 | 5 | S | 4 | $\gamma$ | 0.10 | B-SUM | 1 | 5 | S | CoM | 8.54 | 5 | 17.22 | 87.12 |
| 20 | 12 | 5 | S | 4 | $\gamma$ | 0.10 | B-SUM | 1 | 5 | L | CoM | 8.25 | 6 | 15.15 | 88.30 |
| **21** | | | | | | | | | | | | 6.90 | 14 | 9.15 | **91.98** |
| 22 | | | | | | | | | | | | 7.00 | 36 | 12.72 | 90.14 |
| 23 | | | | | | | | | | | | 6.64 | 42 | 12.60 | 90.38 |
| 24 | | | | | | | | | | | | 6.15 | 49 | 12.28 | 90.79 |
| 25 | | | | | | | | | | | | 6.06 | 58 | 11.59 | 91.18 |

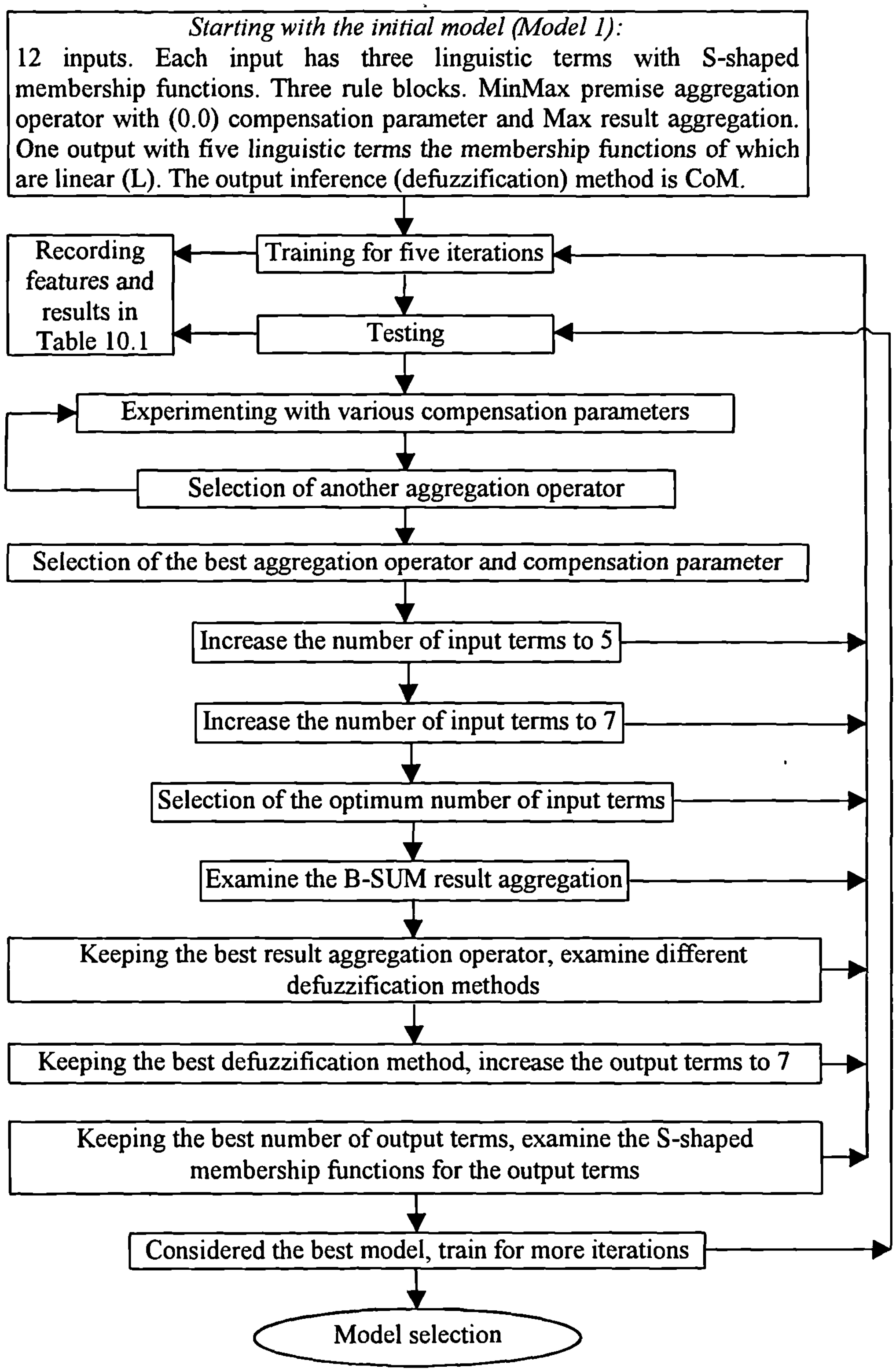



Fig. 7.8: The modification process

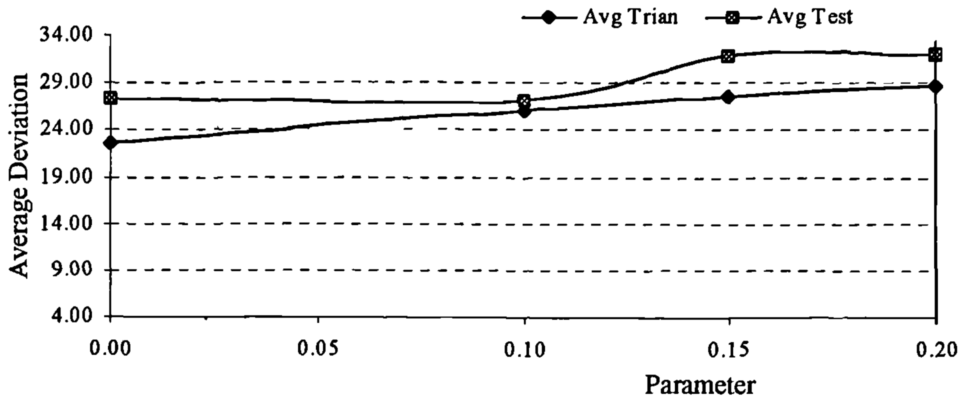



Fig. 7.9: Examining different parameters for the Min-Max operator

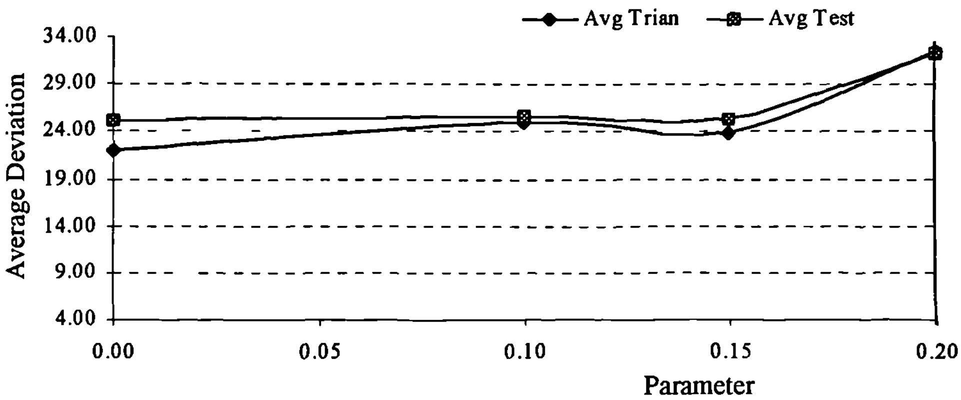



Fig. 7.10: Examining different parameters for the Min-Avg operator

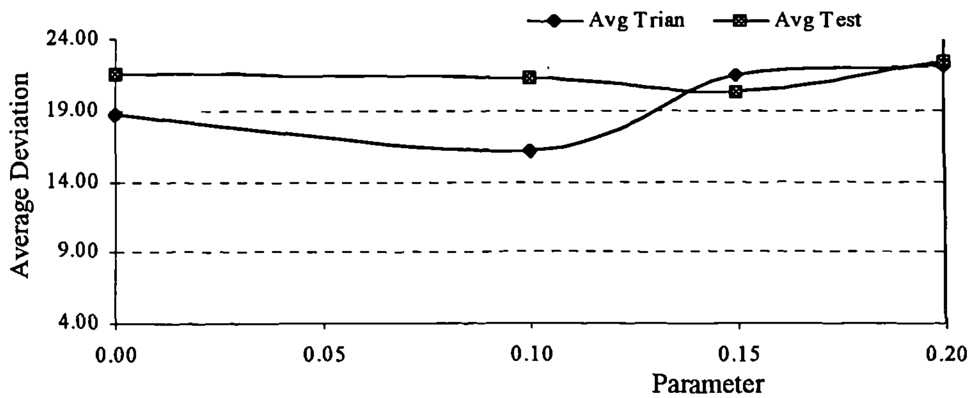



Fig. 7.11: Examining different parameters for the "γ" operator

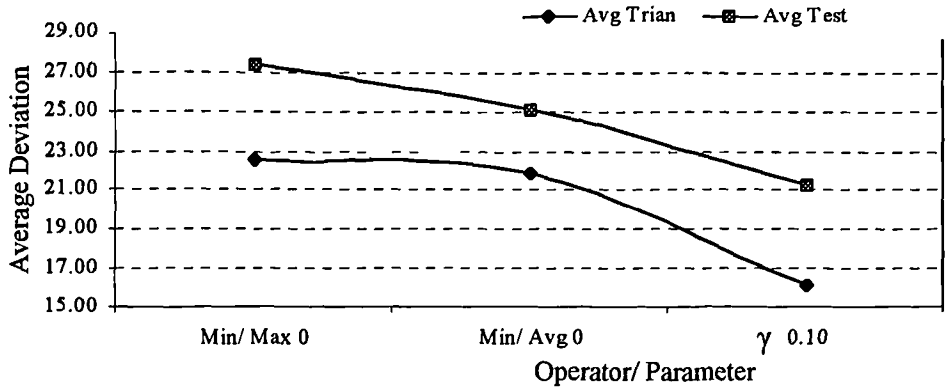



Fig. 7.12: Selection of the best operator and parameter

4. Keeping the "γ" aggregation operator with (0.10) compensation parameter, the number of input liguistic terms was increased from three to five terms and then to seven. Five input terms (Model 13) are more suitable compared to three (Model 10) and seven (Model 14) as illustrated in Fig.7.13.

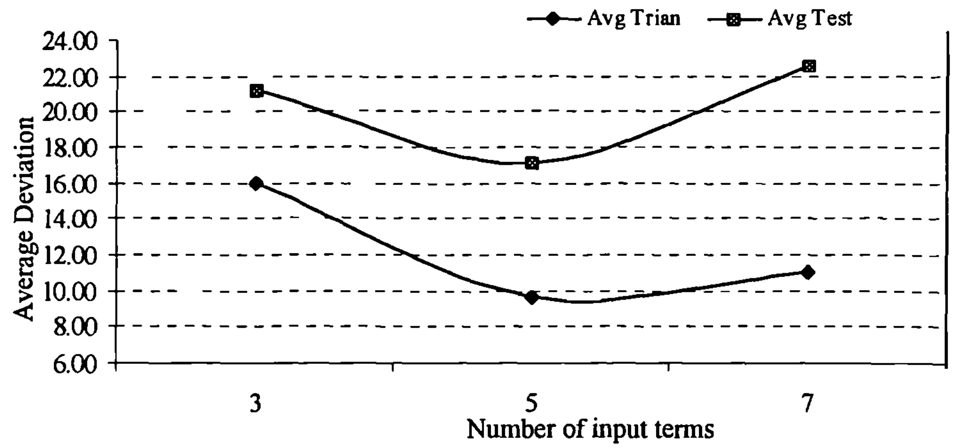



Fig. 7.13: Examining different number of input terms

5. Using five input terms, the bounded sum (B-Sum) result aggregation operator (see section 2.8.1.2.2) was tested. The B-Sum operator (Model 15) is more suitable than the Max operator (Model 13) as shown in Fig. 7.14.
6. Different output inference, i.e. defuzzification, methods were experimented with (Models 16 to 17). The "Mean of Maximum" (MoM) method has the highest training and testing performances as illustrated in Fig. 7.14. However, this method was not adopted due to its discontinuity property.

A small change to an input variable might cause an abrupt change in the output variable (see Section 2.8.1.3). Therefore, the CoM method is still the most suitable one.

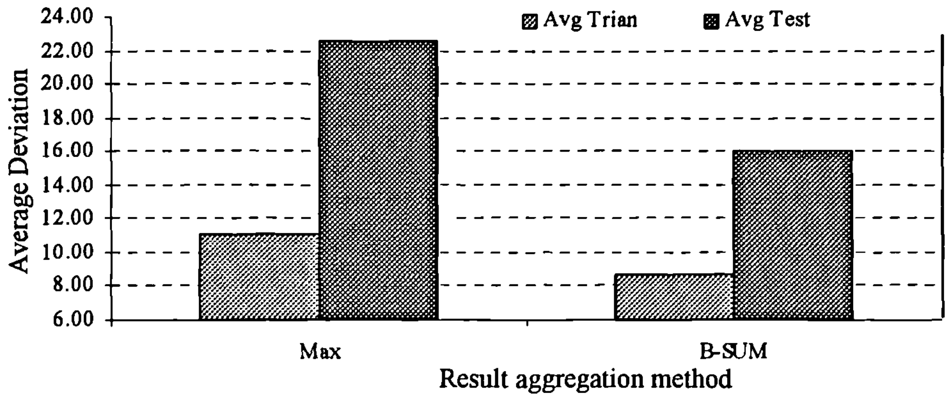



Fig. 7.14: Selection of the best result aggregation method

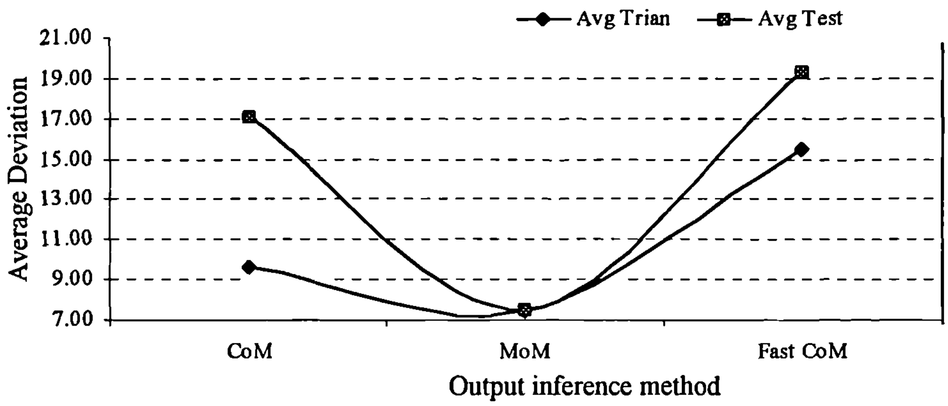



Fig. 7.15: Examining different defuzzification methods

7. The number of output terms was increased to seven (Model 18). However, Five terms are more appropriate (see Fig. 7.16).

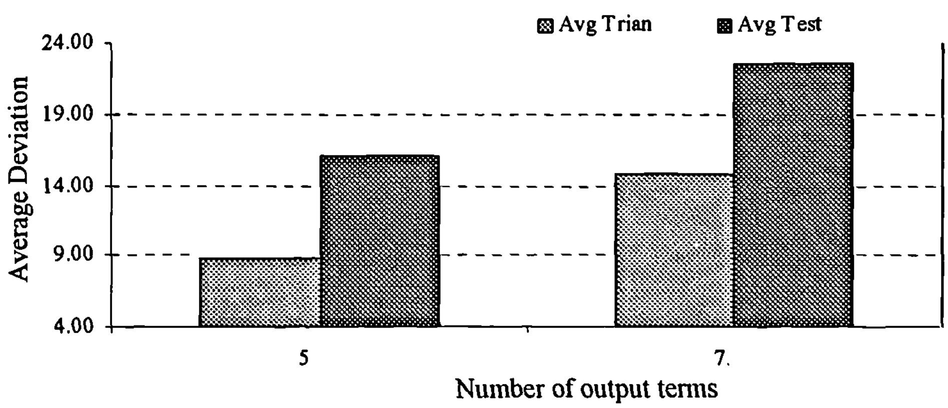



Fig. 7.16: Examining different number of output terms

9. The type of membership functions of the output linguistic terms was modified from linear to non-linear, i.e. S shape, (Model 19) without any improvement. The linear (L-shape) is still, although slightly, more suitable as suggested by Fig. 7.17.

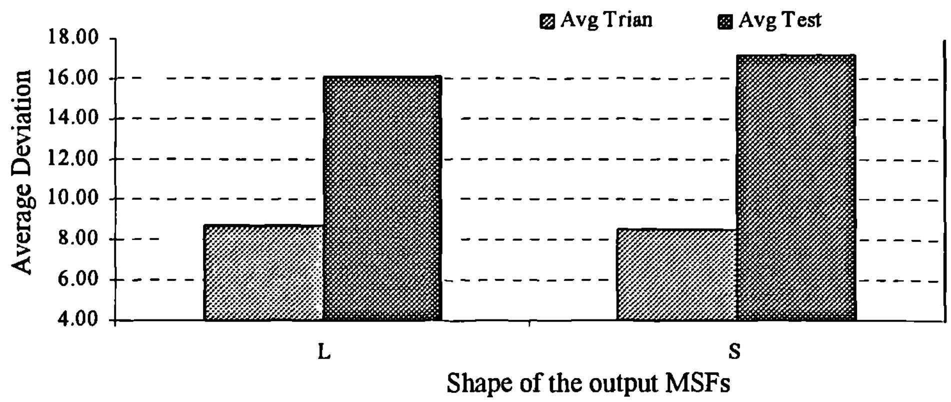



Fig. 7.17: Selection of the output membership functions' shape

10. The best model developed up to this stage is Model 15 (see Table 7.1). Therefore, it was considered for more training iterations (Models 20 to 25).

So far, numerous combinations of potential model characteristics were systematically examined. Nevertheless, although it might improve the model accuracy, no attempt was made to consider more or less input variables. Only those variables considered in the final ANN "bid/ no bid" model were considered. It was believed that it is not necessary to examine different input variables because of the following reasons:

1. A correlation analysis performed in section 6.4.1.1.1 proved that these variables are the most influential ones;
2. The main objective of this chapter is only to investigate the feasibility of applying the neurofuzzy technique to the bidding process to solve the implicity problem of the ANN model; and,
3. The considered input variables enabled the development of a highly accurate model.

The performances of all the experimented with model were analysed and the best model was selected as explained in the next section.

### 7.2.5 Model Selection

The selection process is based on the following criteria:

- High performance in the training stage (low $Ave.Dev._{Training}$); and,
- High performance in the testing stage (low $Ave.Dev._{Testing}$).

A subjective index called the performance index (PI) was developed to help in selection of the best model in a systematic way. The performance index is produced using the following formula:

$$PI=100-\frac{Ave.\_Dev._{Training}+Ave.\_Dev._{Testing}}{2} \qquad (7.1)$$

The PI was computed for all the twenty five developed models during the modification phase. Models 16 has the highest performance index among all the other models as illustrated in Fig.7.18. However, it was not selected due to the discontinuity of its defuzzification method (see sections 2.8.1.3 and 7.2.4). Instead, Model 21 was selected as the best model.

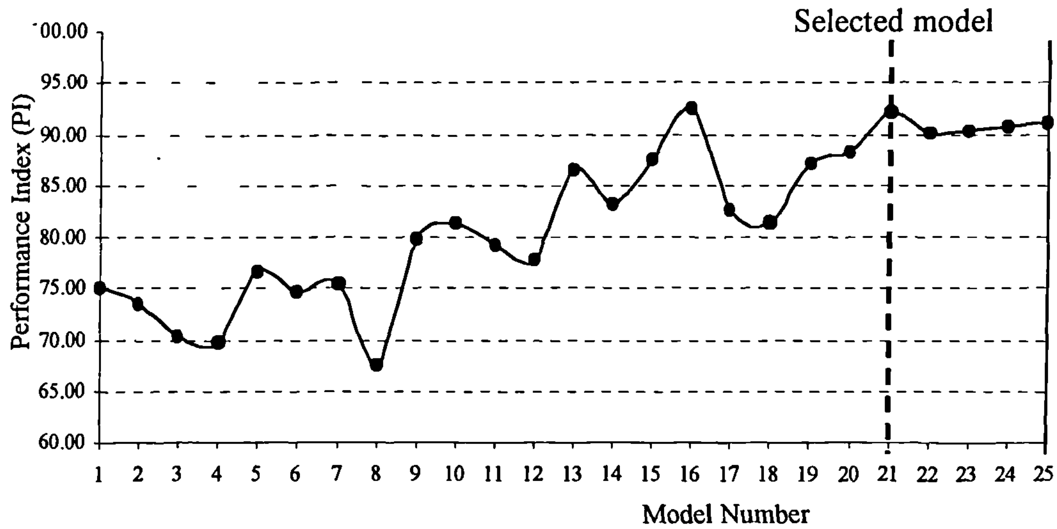



Fig. 7.18: Selection of the final neurofuzzy bid/no bid model

### 7.2.6 The Final Fuzzy Logic "Bid/No Bid" Model

This section is devoted to describing the structure and the main properties of the selected model (Model 21). The system structure identifies the fuzzy logic inference flow from the input variables to the output variable. The fuzzification in the input interfaces translates real inputs, e.g. 3, into fuzzy values, e.g. Medium. The fuzzy inference takes place in rule blocks, which contain the linguistic control rules. These rules share one output variable (neurofuzzy bidding index). Fig. 7.19 shows the whole structure of this fuzzy system including input interfaces, rule blocks and the output interface. The connecting lines symbolise the data flow.

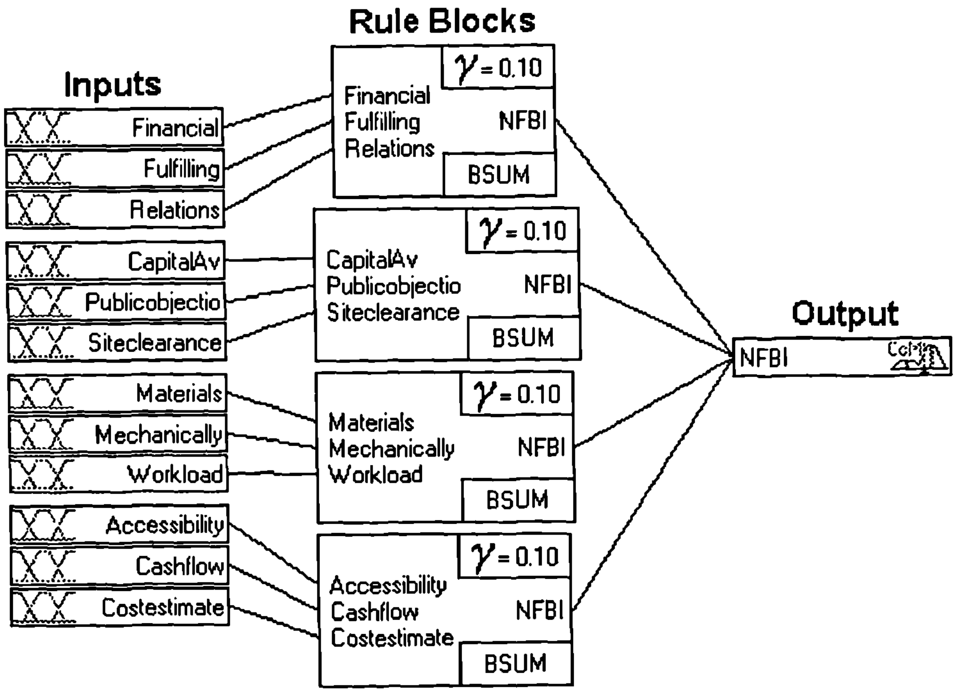



Fig. 7.19: Structure of the "bid/no bid" fuzzy logic system

The model has twelve input variables (set S2 in Table 6.2). Each one of the input variables has five liguistic terms (Very Low, Low, Medium, High, and Very High) with S-shaped MBFs. Fig. 7.20 shows the MBFs of the "Workload" linguisitc varible as an example of the model inputs

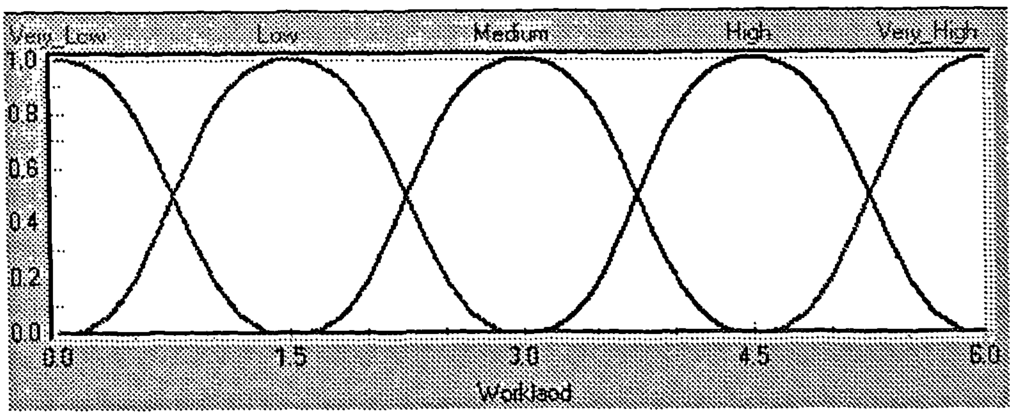



Fig. 7.20: MBFs of the "workload" input variable

The model has four rule blocks, which contain the control strategy of the fuzzy logic system. Each rule block confines all rules that are for the same context. A context is defined by the same input and output variables of the rules. The rules' "if" part, i.e. premise, describes the situation, for which the rules are designed. The "then" part, i.e. result, describes the response of the fuzzy system in this situation. The DoS is used to weigh each rule according to its importance. The processing of the rules starts with calculating the "if" part. The operator type of the rule block determines which method is used. There are three operator types (MIN-MAX, MIN-AVG and GAMMA). The characteristics of each operator type are influenced by the selected compensation parameter (see section 2.8.1.2.1). The GAMMA ($\gamma$) primes aggregation operator with (0.10) compensation parameter and the bounded sum (B-Sum) result aggregation operator were used in all the rule blocks. Tables 7.2 to 7.5 show the rules and their degrees of support of the system rule blocks sorted in a descending order of importance, i.e. DoS.

Table 7.2: Rules of rule block "RB1"

| IF | | | THEN | |
|---|---|---|---|---|
| **Financial** | **Fulfilling** | **Relations** | **DoS** | **NFBI** |
| Very_low | Very_low | Very_low | 1.00 | Very_Low |
| Very_low | Very_low | Very_low | 0.99 | Low |
| Very_low | Very_low | Very_low | 0.91 | Medium |
| Very_low | Very_low | Very_low | 0.57 | High |
| Very_low | Very_low | Very_low | 0.27 | Very_High |
| Very_low | Very_low | Low | 0.15 | Very_Low |
| Very_low | Very_low | Low | 0.10 | Low |
| Very_low | Very_low | Low | 0.03 | Medium |
| Very_low | | | 1.00 | Very_Low |
| Low | Low | Medium | 0.13 | Very_Low |
| Low | Medium | Very_low | 0.19 | Very_Low |
| Low | Medium | Low | 0.02 | Very_Low |
| Low | Medium | High | 0.35 | Low |
| Low | Medium | High | 0.95 | Very_Low |
| Medium | Medium | Low | 0.16 | Very_Low |
| Medium | Medium | Medium | 0.26 | Very_Low |
| Medium | Very_high | Low | 0.06 | Very_High |
| Medium | Very_high | Medium | 0.34 | Very_High |
| Medium | Very_high | High | 0.02 | Very_High |
| Medium | Very_high | Very_high | 0.03 | High |
| High | Medium | Very_high | 1.00 | Very_High |
| High | High | Low | 1.00 | Very_Low |
| High | Very_high | Medium | 0.01 | Very_High |
| High | Very_high | High | 0.02 | Very_High |

| | | | | |
|---|---|---|---|---|
| Very_high | Very_low | Medium | 0.05 | Low |
| Very_high | High | Very_high | 0.02 | Very_High |
| Very_high | Very_high | Low | 0.04 | Very_High |
| Very_high | Very_high | Very_high | 0.06 | Very_High |
| Very_high | | | 0.24 | Very_High |
| | Very_low | | 1.00 | Very_Low |
| | Low | | 1.00 | Very_Low |
| | | Very_low | 0.30 | Very_Low |
| | | Very_high | 1.00 | Very_High |

Table 7.3: Rules of rule block "RB2"

| IF | | | THEN | |
|---|---|---|---|---|
| **CapitalAv** | **Publicobjection** | **Siteclearance** | **DoS** | **NFBI** |
| High | High | Low | 0.74 | Low |
| Low | Very_low | Very_low | 0.61 | Very_Low |
| Low | Low | Medium | 0.03 | Very_Low |
| Low | Medium | High | 0.04 | Very_High |
| Very_low | | | 0.43 | Very_Low |
| Very_high | | | 0.09 | Very_High |
| | Very_high | | 0.38 | Very_Low |
| | | Very_low | 0.84 | Very_Low |
| | | Very_high | 0.14 | Very_High |

Table 7.4: Rules of rule block "RB3"

| IF | | | THEN | |
|---|---|---|---|---|
| **Materials** | **Mechanically** | **Workload** | **DoS** | **NFBI** |
| High | High | Low | 1.00 | Very_High |
| Very_low | | | 1.00 | Very_Low |
| Low | | | 1.00 | Low |
| Very_high | | | 0.37 | Very_High |
| | Very_low | | 0.46 | Very_Low |
| | Very_high | | 1.00 | Very_High |
| | | Very_Low | 1.00 | Very_High |
| | | Very_High | 1.00 | Very_Low |

Table 7.5: Rules of rule block "RB4"

| IF | | | THEN | |
|---|---|---|---|---|
| **Accessibility** | **Cashflow** | **Costestimate** | **DoS** | **NFBI** |
| Low | High | Medium | 0.96 | Very_Low |
| Low | Medium | Medium | 1.00 | Very_Low |
| Low | Medium | High | 0.51 | Very_Low |
| Very_low | | | 0.57 | Very_Low |
| Very_high | | | 0.17 | Very_High |
| | Very_low | | 0.87 | Very_Low |
| | Very_high | | 0.05 | Very_High |
| | | Very_low | 0.61 | Very_Low |
| | | Very_high | 0.01 | Very_High |

The output of the rule blocks is a linguistic value, e.g. medium slightly high. The defuzzification in the output interface translates it into real value, e.g. NFBI=3.25, using the output linguistic terms. Fig. 7.21 shows the output linguistic variable, which is constructed of five linear membership functions (Very Low, Low, Medium, High, and Very High).

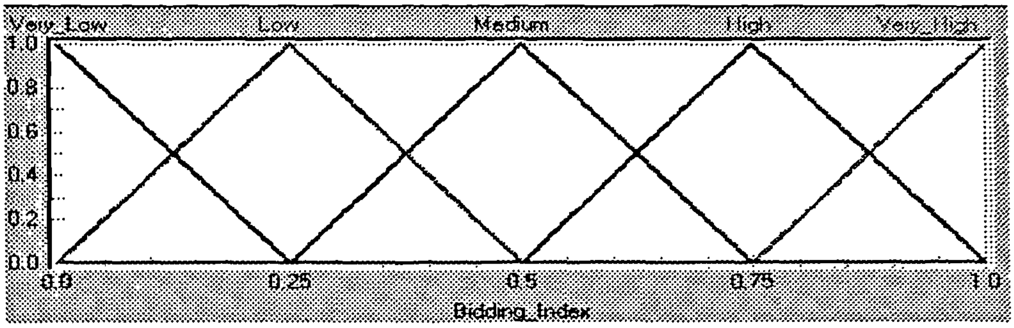



Fig. 7.21: MBF of the output variable "NFBI"

The following section explains how the best cut-off point between "bid" and "no bid" recommendations was identified and how the quality of the model's output was improved through the development of a sub-model that assesses the confidence degree in each recommendation made by the main model.

### 7.2.7 Confidence Degree Sub-Model

This section explains briefly the development of a sub-model that is able to assess the confidence degree of each bidding recommendation made by the principal model. The main components of this sub-model are the best cut-off point between "bid" and "no bid" decisions (X), a point above which the confidence in "bid" is 100% (X1), and a point below which the confidence in "no bid" is 100% (X2). To select the best possible values of X, X1, and X2, the developed model (Model 21) was used to produce bidding indices for the one hundred and sixty two real projects used in training. Different X values were experimented with. The number of unsuccessful recommendations was recorded for each experiment as shown in Table 7.6.

Table 7.6: Selection of the best cut-off point between "bid" and "no bid"

| Point | | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Unsuccessful decisions | Train | 36 | 15 | 11 | 8 | 8 | 9 | 9 | 9 | 10 | 11 | 19 |
| | Test | 7 | 2 | 2 | 2 | 1 | 1 | 2 | 1 | 1 | 2 | 3 |

The minimum number of unsuccessful recommendations (8) corresponds to (X=0.3 and X=0.4). X was set to (0.4) because it also corresponds to the minimum number of unsuccessful recommendations for the testing projects as shown in Fig. 7.22. Examining the neurofuzzy bidding indices of the training samples revealed that all contractors decided to bid when NFBI = 1, which was considered to be X1. On the other hand, all contractors decided not to bid when NFBI = 0., which was considered to be X2.

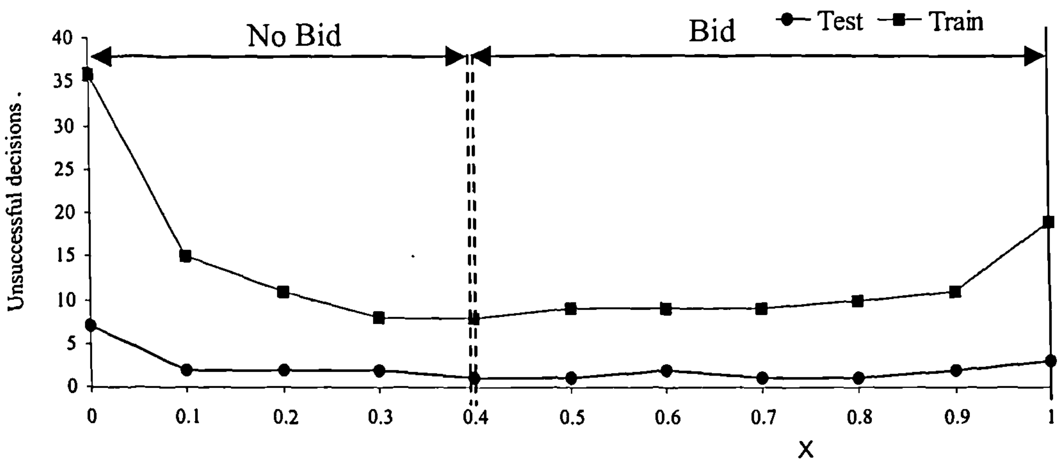



Fig. 7.22: Selection of the best cut-off point between "bid" and "no bid"

The degree of confidence between NFBI = 0 and NFBI = 0.40 and between NFBI = 0.40 and NFBI = 1 was considered to be a linear function. Based on this assumption and on the values selected for X, X1 and X2, a confidence model was developed as illustrated in Fig. 7.23.

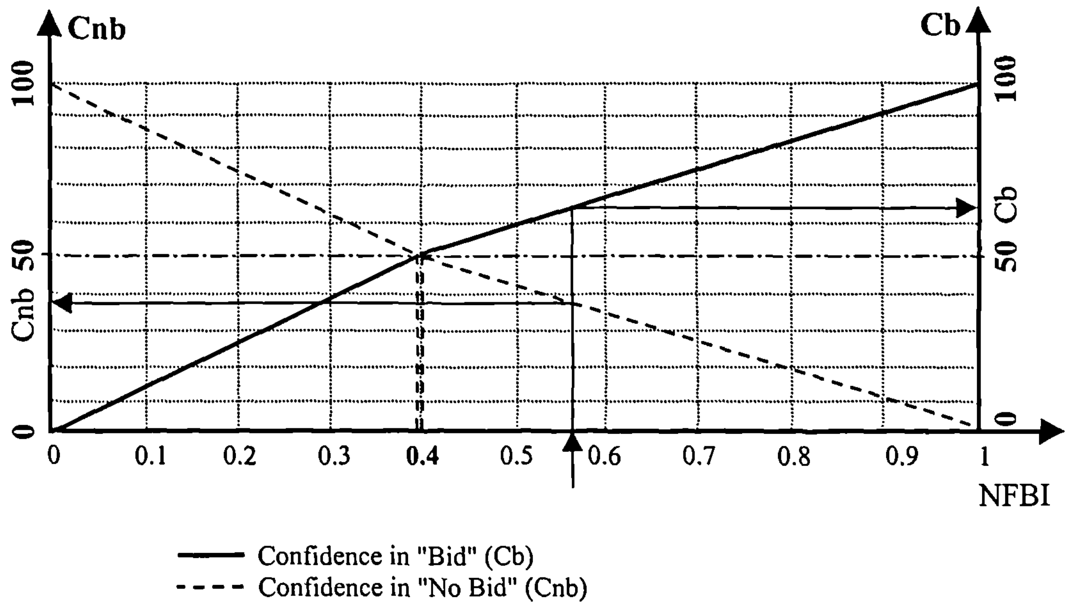



Fig. 7.23: Confidence degrees in "bid" and "no bid"

Fig. 7.23 can be articulated as follows:

If NFBI<0.4, then Cb = 1.25 *NFBI (7.3)

If NFBI > 0.4, then Cb = 0.8333*NFBI + 0.1667 (7.4)

Cnb = 1- Cb (7.5)

Where:

Cb is the degree of confidence in "bid" recommendation; and,

Cnb is the degree of confidence in "no bid" recommendation.

The following section investigates the effect of individual input variables on the model's output through a simple sensitivity analysis procedure.

### 7.2.8 Sensitivity Analysis

This section investigates the effect of changes in individual input variables on the recommendation made by the developed model. In a similar approach to which has been implemented in section 6.4.2.3, a set of neutral input values for which the model produces a NFBI equal to (0.4), i.e. degree of confidence in both "bid" and "no bid" recommendations is equal to 50%, were selected by modifying the original neutral score suggested by Syrian contractors. Formula (6.18) was implemented. The corresponding constant (a = -1.378) was identified through an iterative trial and error process. The new neutral values are listed in column 5 of Table 7.7. The neurofuzzy bidding index (NFBI) produced for these values by the developed model is (0.40), i.e. the degree of confidence in both "bid" and " no bid" recommendations is 50%. To uncover the model's response to changes in its inputs, each input was assigned six scores (0, 1, to 6) while setting the other inputs to their neutral scores. First, factor (F1) was assigned a (0) score while setting the other factors to their neutral scores. The corresponding output (NFBI) was recorded in columns 6 of Table 7.7. Then scores 1 to 6 were tested and the results were recorded in column 7 to 12 respectively. The same process was repeated for all the input variables. The model's responses to changes in its input variables are shown in Fig. 7.24.

Table 7.7: Analysis of the effect of changes in the input variables on the neurofuzzy model's output

| Bid/No Bid Criteria | | Neutral Scores | | | Scores between 0 and 6 | | | | | | | $SI_i$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| No. | Name | $StD_i$ | $B_i$ | $B_i'$ | 0 | 1 | 2 | 3 | 4 | 5 | 6 | |
| F1 | Fulfilling the to-tender conditions | 0.370 | 5.840 | 5.330 | 0.070 | 0.070 | 0.077 | 0.177 | 0.220 | 0.307 | 0.472 | 0.401 |
| F2 | Site accessibility | 1.030 | 3.000 | 1.581 | 0.192 | 0.334 | 0.401 | 0.401 | 0.401 | 0.436 | 0.549 | 0.357 |
| F3 | Site clearance of obstructions | 0.900 | 3.640 | 2.400 | 0.152 | 0.309 | 0.404 | 0.398 | 0.404 | 0.435 | 0.533 | 0.380 |
| F4 | Availability of capital required | 0.730 | 3.410 | 2.404 | 0.222 | 0.341 | 0.394 | 0.406 | 0.406 | 0.426 | 0.497 | 0.275 |
| F5 | Availability of materials required | 0.900 | 3.560 | 2.320 | 0.101 | 0.279 | 0.337 | 0.835 | 0.835 | 0.892 | 0.956 | 0.854 |
| F6 | Proportions that could be constructed mechanically | 0.720 | 3.050 | 2.058 | 0.213 | 0.343 | 0.401 | 0.401 | 0.401 | 0.563 | 0.777 | 0.564 |
| F7 | Confidence in the cost estimate | 0.730 | 3.850 | 2.844 | 0.185 | 0.328 | 0.401 | 0.401 | 0.401 | 0.405 | 0.409 | 0.224 |
| F8 | Financial capability of the client | 0.880 | 3.480 | 2.267 | 0.070 | 0.162 | 0.314 | 0.494 | 0.401 | 0.510 | 0.520 | 0.450 |
| F9 | Public objection | 0.750 | 2.150 | 1.117 | 0.406 | 0.401 | 0.401 | 0.405 | 0.404 | 0.355 | 0.235 | -0.171 |
| F10 | Current work load | 0.750 | 2.900 | 1.867 | 0.777 | 0.561 | 0.401 | 0.401 | 0.401 | 0.292 | 0.140 | -0.638 |
| F11 | Relation with/ reputation of the client | 0.730 | 3.840 | 2.834 | 0.136 | 0.236 | 0.309 | 0.406 | 0.293 | 0.488 | 0.777 | 0.641 |
| F12 | Favourability of the cash flow | 1.080 | 2.800 | 1.312 | 0.153 | 0.312 | 0.287 | 0.141 | 0.140 | 0.171 | 0.470 | 0.317 |

Where:

$B_i$ is the main of the values suggested for the neutral score for factor Fi through questionnaire A;
$StD_i$ is the standard deviation of the values suggested for $B_i$;
$B_i' = B_i + a * StD_i$ is the modified neutral score for $F_i$;
a is a modification constant (a = -1.378); and,
$SI_i$ is the sensitivity index of factor $F_i$.

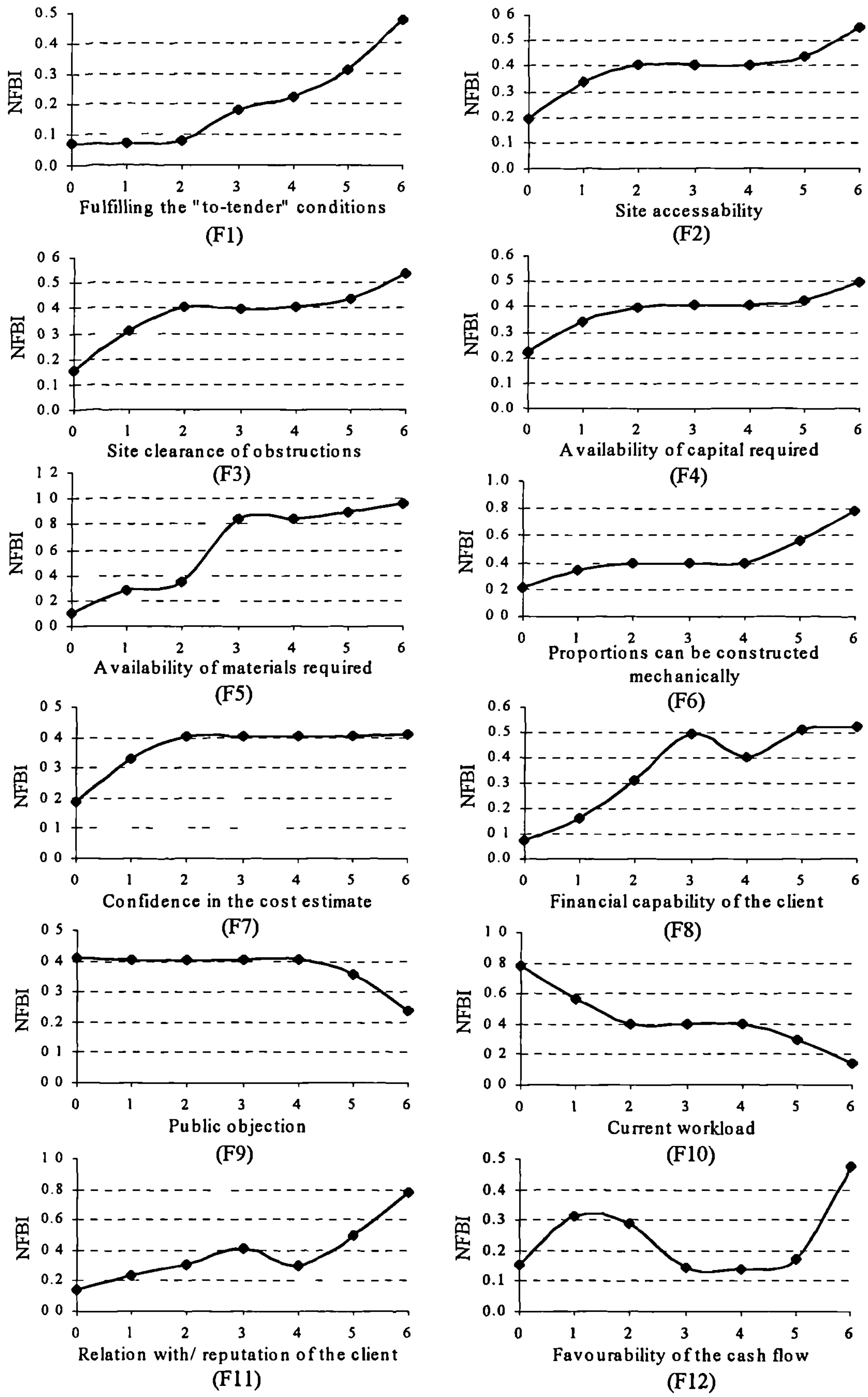



Fig. 7.24: Sensitivity of the neurofuzzy "bid/no bid" model to changes in individual input variables

The difference between the NFBIs for (0) and (6) scores assigned to an input variable ($F_i$) indicates the overall sensitivity of the model's output to changes in this variable. Therefore, an index called the sensitivity index (SI) was computed for each input variable ($F_i$) using the following equation:

$$SI_i = NFBI\,(6)_i - NFBI\,(0)_i \tag{7.6}$$

The sensitivity indices are listed in the last column of Table 7.7 and illustrated in Fig. 7.25.

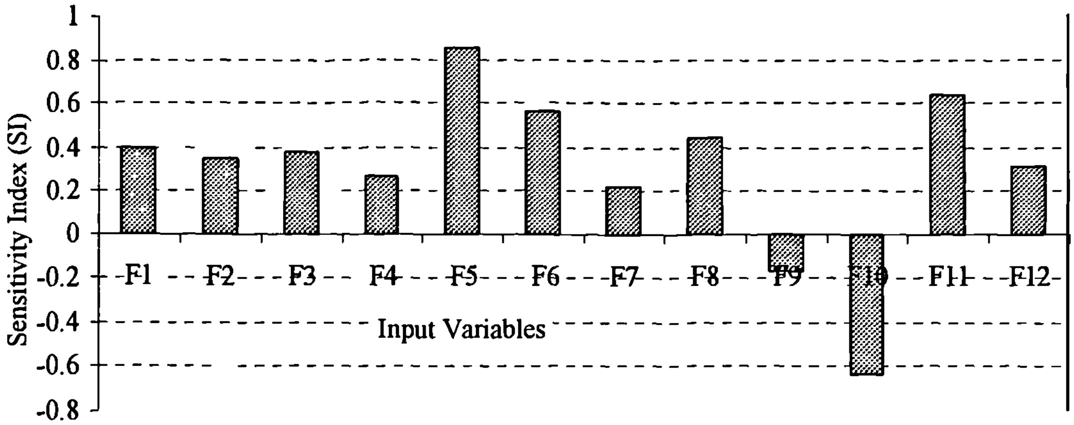



Fig. 7.25: Effect of individual inputs on the neurofuzzy "bid/no bid" model's output

A careful observation of Fig. 7.24 reveals that the developed model has some minor drawbacks. These include the following:

- A medium financial capability of the client in a certain bidding situation will lead to a "bid" recommendation with a reasonable degree of confidence. But, increasing the score from "medium" ,i.e. 3, to "high" score ,i.e. 4, for this factor will decrease the confidence in the "bid" recommendation (see Fig. 7.24 F8);
- A medium score of the "relation with/reputation of the client" factor does not encourage nor discourage the "bid" recommendation. Increasing this score to high (4) will cause a drop in the neurofuzzy bidding index before it rises again for higher scores (see Fig. 7.24 F11); and,
- The "favourability of the expected cash flow" factor decreases the NFBI index when assigned "low", to "very high" scores. It will cause a rise in this index only for "extremely high" scores (see Fig. 7.24 F12).

These irregularities can be due to some noise in the training data. The model failed to avoid introducing this noise to its knowledge base. One way to solve this problem is by using the clustering techniques. The small training sample hindered pursuing this solution. Another useful conclusions can be drawn from Fig.7.24 and Fig. 7.25. These are summarised as follows:

- Fulfilling the to-tender conditions has only a moderate SI as shown in Fig. 7.25. Nevertheless, it has a crucial effect on the model's recommendation because it is enough, while the other variable set to their neutral scores, to cause a "no bid" recommendation unless it is assigned very high scores as shown in Fig. 7.24 F1.
- High current workload (F10) will discourage the "bid" recommendation for new projects; and,
- Good relation with and reputation of a client generally encourages the "bid" recommendation for projects with him/her.

These characteristics could not be captured by the ANN model (see section 6.4.2.3). Moreover, some very detailed features of the bidding practice are accounted for by the neurofuzzy model. For example, good relations with the client can compensate for lower fulfilment of the to-tender conditions imposed by the client as indicated by Fig. 7.26, which shows the relation between these two variables and the neurofuzzy bidding index. The entire knowledge base of the developed model can be visualised in the same way. Fig. 7.27 shows that very low workload might force risking a "bid" decision although poor fulfilment of the to-tender conditions. On the other hand, complete fulfilment of these conditions is not enough to cause a "bid" decision when the current workload is very high. This explicit knowledge representation is one of the main advantages of the fuzzy logic systems.

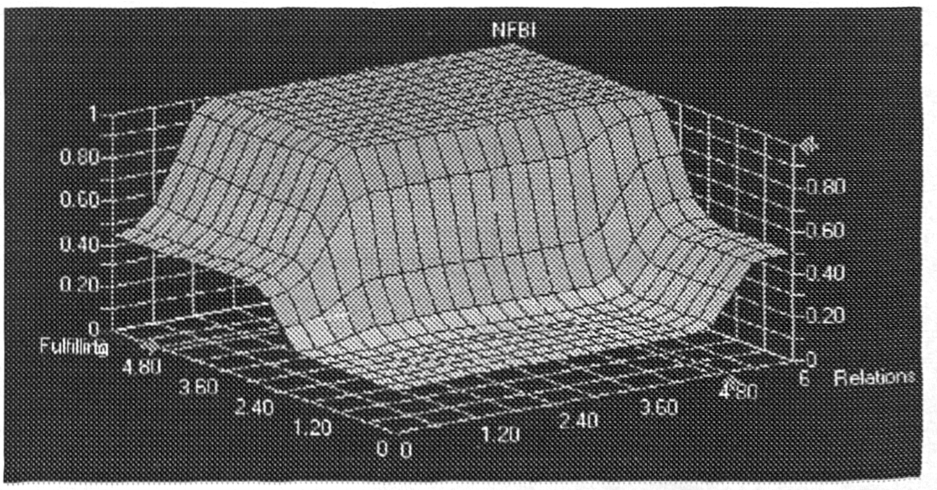



Fig. 7.26: Relationship between "fulfilment the to-tender conditions"

Also, the rules base and the visualisation of these rules do not leave any aspect of the model behaviour unexplained, which is another advantage over the "black-box"-featured ANN models.

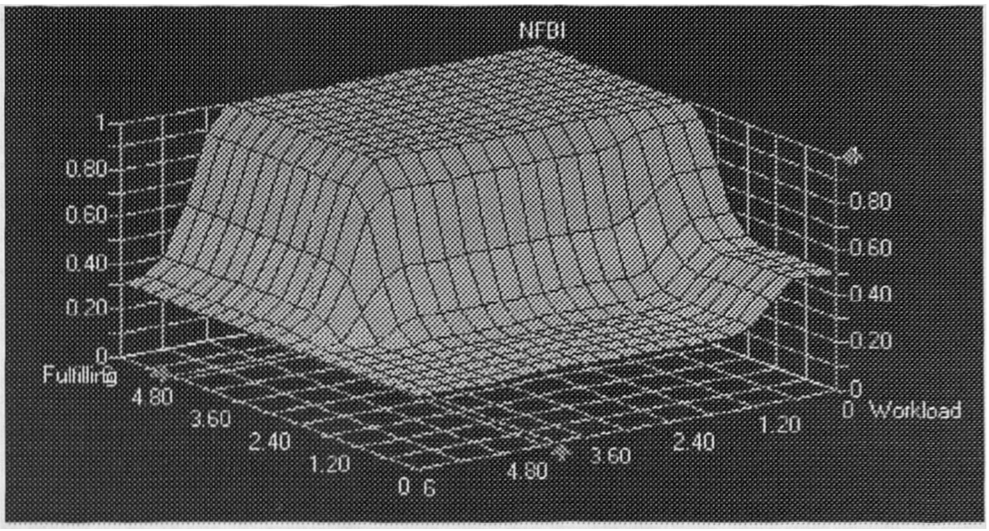



Fig. 7.27: Relationship between "fulfilment the to-tender conditions", "current workload", and the "neurofuzzy bidding index"

The robustness of the developed neurofuzzy model is farther proved by a very high accuracy in simulating the actual decisions of the test projects, which have not been used in the training process as explained in the following section.

### 7.2.9 Testing and Validation

The same real life twenty bidding situations used to test the paramtetric and the ANN bid/no bid models were used to test the final fuzzy "bid/no bid" model. The contractor's assessments were presented to the developed main model, which produced a neurofuzzy bidding index (NFBI) for each bidding situation. The computed NFBI was passed to the complementary confidence model to compute the corresponding degree of confidence. Table 7.8 shows the recommendations and the degrees of confidence produced for the twenty test cases. Fig. 7.28 illustrates the actual and predicted decisions of these cases. The model miss-predicted the actual decision for one bidding situation (No. 10) and simulated accurately the actual decisions of the remaining situations. But, even though a bid was submitted for project 13, the bid was rejected in real life by the client. The other submitted bids were accepted. Thus, it can concluded that the fuzzy model recommended the desired "bid/no bid" decisions of eighteen out of twenty bidding situations, i.e. 90% accuracy. This is the same accuracy of the ANN model. However, the degrees of confidence in the "bid" recommendation made by the fuzzy model for cases number 10 and (73.14%) is lower than the degree of confidence in the "bid" recommendation made by the ANN model for the same project.

Table 7.8: Actual and predicted decisions of twenty unforeseen bidding situations

| Project No. | Actual decision | NFBI | Predicted decision | Confidence degree (%) | Notes |
|---|---|---|---|---|---|
| 1 | Bid | 1.00 | Bid | 100.00 | |
| 2 | Bid | 0.84 | Bid | 86.78 | |
| 3 | Bid | 1.00 | Bid | 100.00 | |
| 4 | Bid | 1.00 | Bid | 100.00 | |
| 5 | Bid | 0.54 | Bid | 61.79 | |
| 6 | Bid | 1.00 | Bid | 100.00 | |
| 7 | Bid | 1.00 | Bid | 100.00 | |
| 8 | No Bid | 0.05 | No Bid | 100.00 | |
| 9 | No Bid | 0.08 | No Bid | 100.00 | |
| **10** | No Bid | 0.68 | Bid | 73.14 | Wrong |
| 11 | Bid | 1.00 | Bid | 100.00 | |
| 12 | Bid | 1.00 | Bid | 100.00 | |
| 13 | Bid | 1.00 | Bid | 100.00 | Rejected |
| 14 | Bid | 1.00 | Bid | 99.93 | |
| 15 | No Bid | 0.39 | No Bid | 100.00 | |
| 16 | No Bid | 0.00 | No Bid | 100.00 | |
| 17 | No Bid | 0.01 | No Bid | 100.00 | |
| 18 | Bid | 1.00 | Bid | 100.00 | |
| 19 | Bid | 1.00 | Bid | 100.00 | |
| 20 | No Bid | 0.00 | No Bid | 100.00 | |

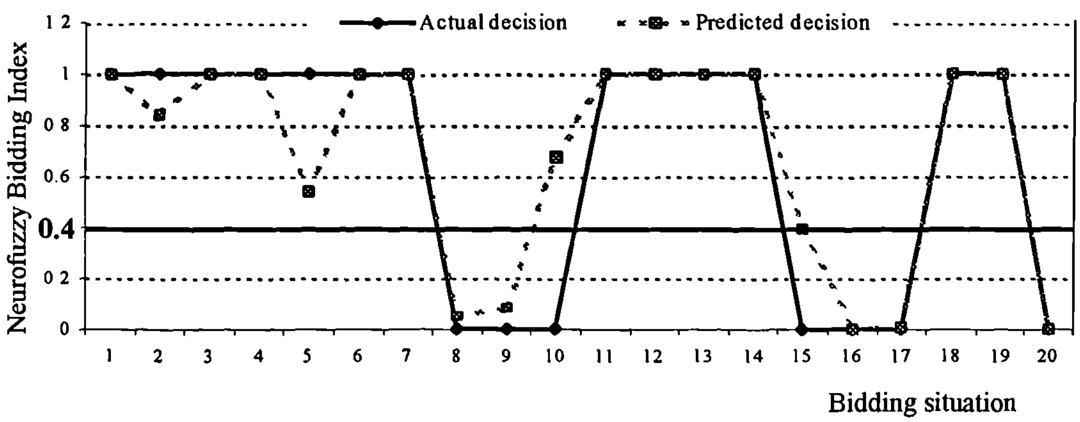



Fig. 7.28: Actual and predicted "bid/no bid" decisions

But the confidence in the "bid" recommendation for project 13, which had been rejected is slightly higher (100% compared to 97.67%). Nevertheless, the clarity of knowledge representation, the ability to hand linguistic and subjective assessments, and the possibility of modifying and optimising the model based on practical experience to suit own requirements and/or changing circumstances are the main advantage of the fuzzy model over the ANN model.

After finalising the fuzzy "bid/ no bid" model, a similar model was developed for the second part of the bidding process (mark up selection) as explained in the following sections.

### 7.3 A Neurofuzzy Model for Mark Up Selection

The same development procedure introduced and implemented in section 7.2 was followed to develop a neurofuzzy model for the mark up side of the bidding problem. The same seven input variables used in the final ANN mark up model were considered in this development process. Also, the same ninety six training bidding situations and the same fifteen randomly selected validation cases were used in training and testing the neurofuzzy models experimented with. Table 7.9 shows the properties, the average training errors, and average testing errors, and the performance indices of twenty five models examined during the modification phase. Seven linguistic terms were more suitable for both of the input variables and the output variable of the mark up model as shown in Fig. 7.29 and Fig. 7.30 Respectively.

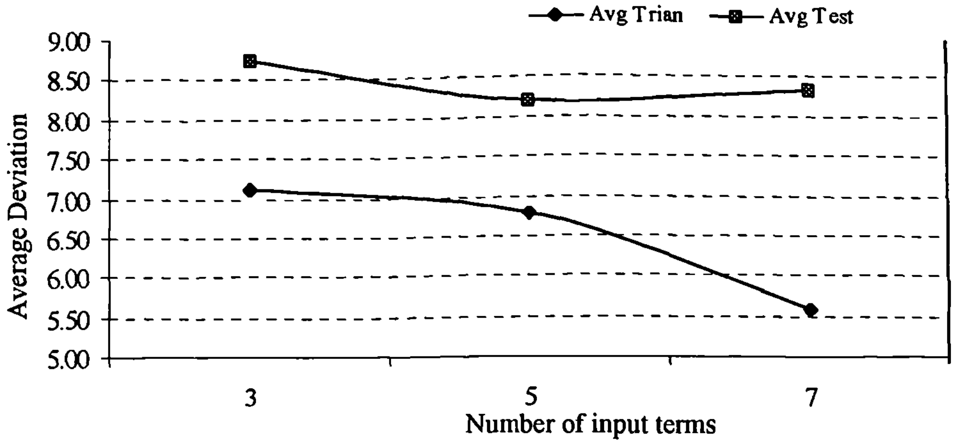



Fig. 7.29: Examining different number of input terms for the mark up model

Table 7.9: Selection of the best structure of the neurofuzzy mark up model

| Model | Inputs | | | Rule Blocks | | | | Outputs | | | | Learning | | Testing | Performance Index (PI) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No. | Terms | | No. | Premise Aggregation | | Result Aggregation | No. | Terms | | Output Inference | Av. Dev. | Iterations | Av. Dev. | |
| | | No. | Shape | | Type | Parameter | | | No. | Shape | | | | | |
| 1 | | | | | | 0.00 | | | | | | 8.10 | | 9.90 | 91.00 |
| 2 | 7 | 3 | | 2 | Min/ Max | 0.10 | | | | | | 7.63 | | 9.13 | 91.62 |
| 3 | | | | | | 0.15 | | | | | | 8.31 | | 10.96 | 90.37 |
| 4 | | | | | | 0.20 | | | | | | 9.26 | | 13.24 | 88.75 |
| 5 | | | | | | 0.00 | | | | | | 8.10 | | 9.90 | 91.00 |
| 6 | 7 | 3 | | 2 | Min/ Avg | 0.10 | Max | | | | | 10.36 | | 10.91 | 89.37 |
| 7 | | | S | | | 0.15 | | | | | | 8.18 | | 9.46 | 91.18 |
| 8 | | | | | | 0.20 | | 1 | 5 | L | CoM | 8.32 | 5 | 9.68 | 91.00 |
| 9 | | | | | | 0.00 | | | | | | 8.07 | | 12.84 | 89.55 |
| 10 | 7 | 3 | | 2 | γ | 0.10 | | | | | | 7.11 | | 8.75 | 92.07 |
| 11 | | | | | | 0.15 | | | | | | 7.68 | | 9.85 | 91.24 |
| 12 | | | | | | 0.20 | | | | | | 7.74 | | 10.72 | 90.77 |
| 13 | 7 | 5 | | 3 | γ | 0.10 | Max | | | | | 6.78 | | 8.21 | 92.51 |
| 14 | 7 | 7 | | 4 | γ | 0.10 | Max | | | | | 5.58 | | 8.33 | 93.05 |
| 15 | 7 | 7 | | 4 | γ | 0.10 | B-SUM | | | | | 7.23 | | 5.76 | 93.51 |
| 16 | 7 | 7 | S | 4 | γ | 0.10 | B-SUM | 1 | 5 | L | MoM | 9.22 | 5 | 9.33 | 90.73 |
| 17 | 7 | 7 | S | 4 | γ | 0.10 | B-SUM | 1 | 5 | L | Fast CoA | 5.60 | 5 | 10.67 | 91.87 |
| 18 | 7 | 7 | S | 4 | γ | 0.10 | B-SUM | 1 | 7 | L | CoM | 5.37 | 5 | 7.11 | 93.76 |
| 19 | 7 | 7 | S | 4 | γ | 0.10 | B-SUM | 1 | 7 | S | CoM | 5.99 | 5 | 6.39 | 93.81 |
| **20** | | | | | | | | | | | | 4.89 | 14 | 4.80 | **95.16** |
| 21 | | | | | | | | | | | | 4.85 | 19 | 6.45 | 94.35 |
| 22 | 7 | 7 | S | 4 | γ | 0.10 | B-SUM | 1 | 7 | S | CoM | 4.82 | 25 | 8.59 | 93.30 |
| 23 | | | | | | | | | | | | 4.84 | 35 | 8.41 | 93.38 |
| 24 | | | | | | | | | | | | 4.71 | 48 | 7.38 | 93.96 |
| 25 | | | | | | | | | | | | 4.59 | 59 | 6.90 | 94.26 |

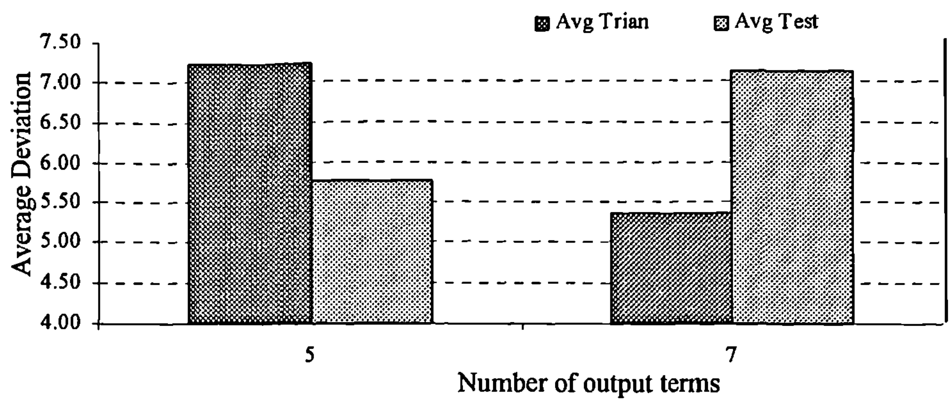



Fig. 7.30: Examining different number of output terms

As shown in Fig. 7.31, the CoM defuzzification method generated more accurate results than the MoM method, which confirms its superiority in qualitative applications (see section 2.8.1.3).

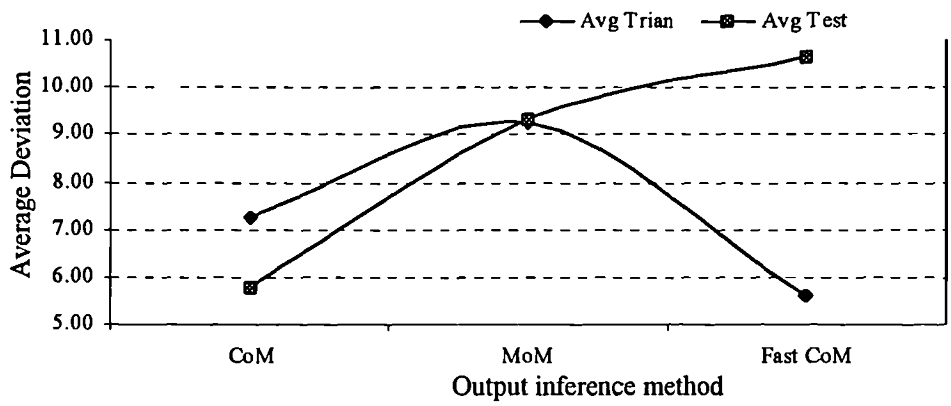



Fig. 7.31: Examining different defuzzification methods

Also, the S-shaped membership functions proved to be slightly more suitable for the output variable as shown in Fig. 7.32.

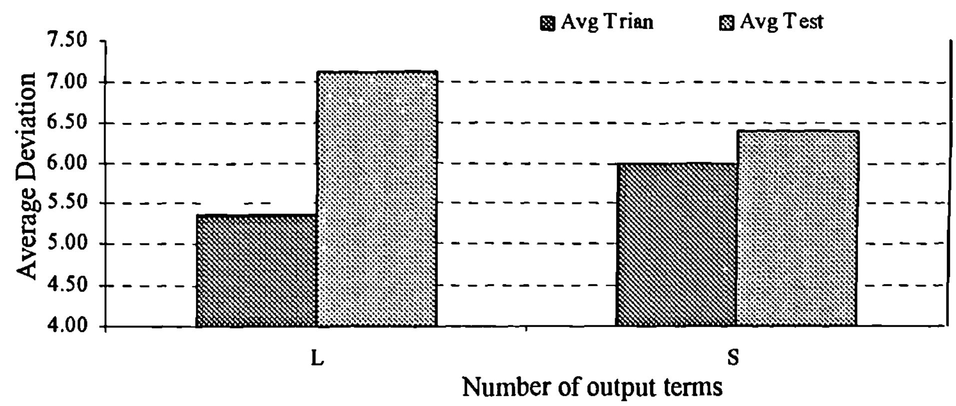



Fig. 7.32: Examining different shapes of membership functions

The "bid/no bid" is a beinary decision whereas two main outputs are expected. On the other hand, the mark up size is selected on a continuous scale. This might be the main reason behind the differences between the number of terms, the defuzzification methods, and the shape of the membership functions of these decisions. Model 20 was selected as the best neurofuzzy mark up model because it has the highest performance index as illustrated in Fig. 7.33. The following section describes the structure and the main properties of the selected model.

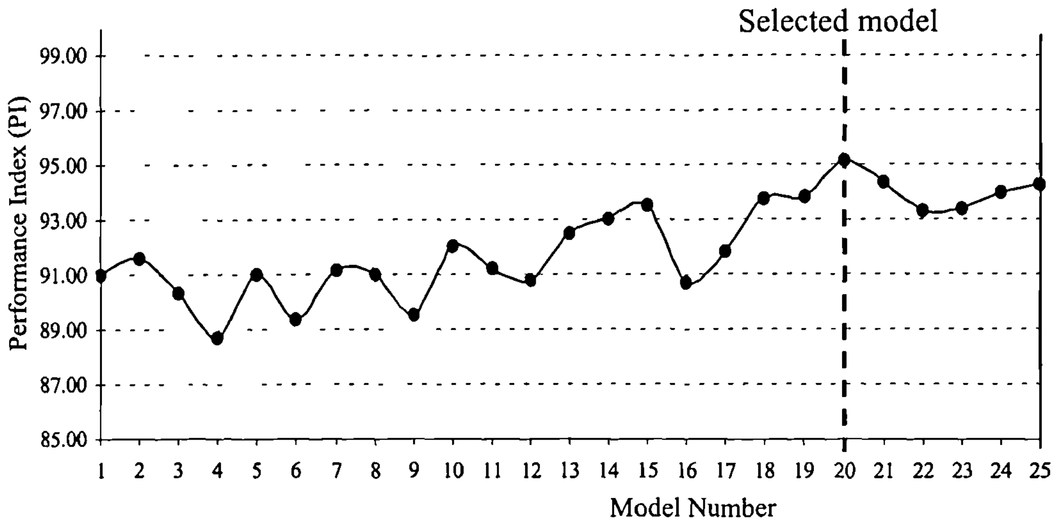



Fig. 7.33: Selection of the final fuzzy mark up model

### 7.3.1 The Final Neurofuzzy Mark up Model

The structure and the main properties of the selected model (Model 20) are explained in this section. Fig. 7.34 shows the general structure of this model. It is constructed of seven linguistic input variables representing the most influential mark up criteria considered in the final ANN mark up model (set S3 in Table 6.13) and one linguistic output variable for the mark up estimation. The connecting lines symbolise the data flow. Each input linguistic variable consists of seven terms (Extremely Low, Very Low, Low, Medium, High, very High, and Extremely High). The membership functions of these terms are S-shaped as illustrated in Fig. 7.35, which shows the "risks expected" linguistic variable as an example of the input variables. The model has four rule blocks, which contain the control strategy of the fuzzy logic system. The operator used for the premise aggregation is of GAMMA type with (0.10) compensation parameter. The bounded sum (B-Sum) result aggregation operator was used in all the rule blocks. Tables 7.10 to 7.13 show the rules and their degrees of support of the system's rule blocks sorted in a descending order of importance, i.e. DoS.

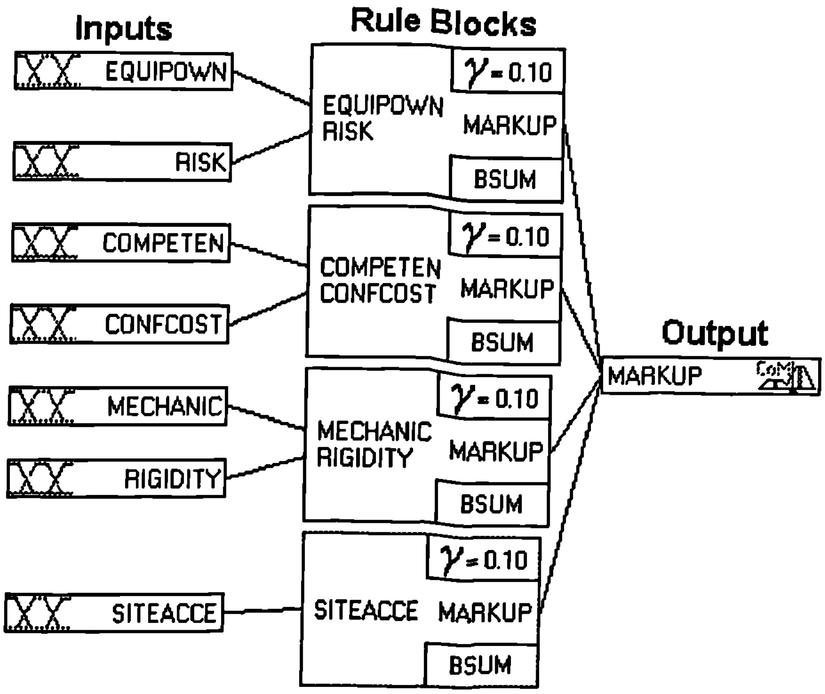



Fig. 7.34: Structure of the fuzzy logic mark up model

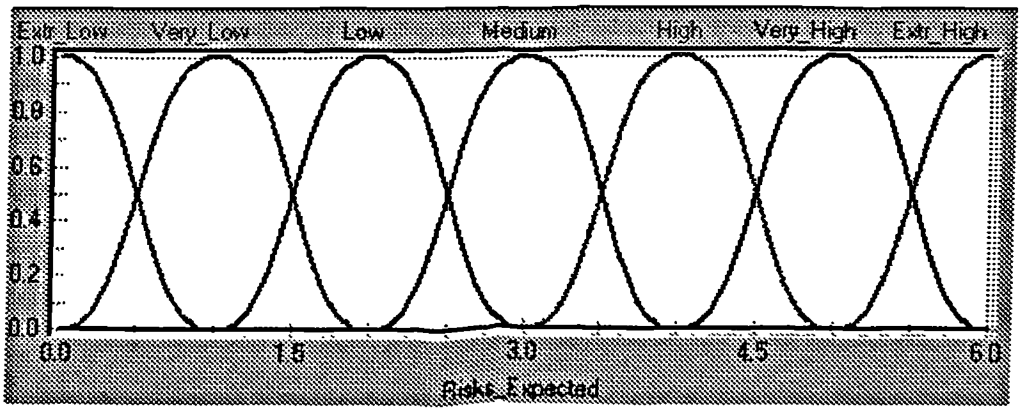



Fig.7.35: MBFs of "Risk expected" input variable

The output of the rule blocks is a linguistic value, e.g. medium slightly low. The defuzzification in the output interface translates it into real value, e.g. Mark up =0.26, using the output linguistic terms. Fig. 7.36 shows the output linguistic variable, which is constructed of seven S-shaped membership functions (Extremely Low, Very Low, Low, Medium, High, Very High, and Extremely High).

Table 7.10: Rules of rule block "RB1"

| IF | | THEN | |
|---|---|---|---|
| EQUIPOWN | RISK | DoS | MARKUP |
| Very_High | Extr_Low | 1.00 | Extr_Low |
| | Extr_High | 1.00 | Extr_High |
| Extr_High | | 1.00 | Very_Low |
| | Very_Low | 0.95 | Low |
| | Medium | 0.81 | Medium |
| Low | Extr_Low | 0.77 | Very_High |
| | Very_High | 0.70 | Very_High |
| Low | High | 0.68 | Very_High |
| Very_High | Very_Low | 0.64 | Extr_Low |
| Very_High | | 0.60 | Very_Low |
| | Extr_Low | 0.60 | Very_Low |
| High | Medium | 0.52 | Extr_Low |
| Extr_Low | High | 0.46 | Extr_High |
| Medium | Medium | 0.43 | Extr_High |
| High | High | 0.41 | Extr_High |
| Very_Low | Medium | 0.36 | Extr_High |
| Medium | Low | 0.35 | Extr_Low |
| Low | High | 0.35 | Extr_High |
| Extr_Low | Very_High | 0.34 | Extr_High |
| Low | Low | 0.31 | Very_High |
| | High | 0.30 | High |
| Medium | High | 0.27 | Extr_Low |
| High | Extr_Low | 0.23 | Extr_High |
| High | Very_Low | 0.21 | Extr_Low |
| Medium | High | 0.15 | Extr_High |
| Extr_Low | Very_High | 0.14 | Very_High |
| Low | High | 0.13 | Extr_Low |
| High | Medium | 0.13 | Extr_High |
| Low | Very_Low | 0.12 | Extr_High |
| Extr_Low | Very_High | 0.12 | Low |
| Very_High | Low | 0.10 | Extr_High |
| Low | Low | 0.10 | Extr_High |
| Medium | | 0.10 | Medium |
| High | | 0.10 | Low |
| Medium | Low | 0.09 | Extr_High |
| High | Very_Low | 0.07 | Extr_High |
| Medium | Very_Low | 0.04 | Very_High |
| Low | | 0.04 | Medium |
| Low | Medium | 0.03 | Extr_Low |
| Extr_Low | Very_High | 0.01 | High |

Table 7.11: Rules of rule block "RB2"

| IF | | THEN | |
|---|---|---|---|
| **COMPETEN** | **CONFCOST** | **DoS** | **MARKUP** |
| Extr_High | | 1.00 | Extr_Low |
| Extr_Low | | 0.90 | Extr_High |
| Very_High | | 0.70 | Very_Low |
| | Extr_High | 0.60 | Extr_Low |
| Very_Low | | 0.50 | Very_High |
| Very_High | Medium | 0.48 | Extr_Low |
| Very_High | High | 0.48 | Extr_Low |
| High | Very_High | 0.44 | Extr_Low |
| Low | | 0.40 | High |
| Very_High | High | 0.33 | Extr_High |
| Medium | | 0.30 | High |
| Very_High | Medium | 0.22 | Extr_High |
| Very_High | Very_High | 0.22 | Extr_Low |
| High | Medium | 0.20 | Very_Low |
| High | High | 0.16 | Very_Low |
| High | Medium | 0.12 | Extr_Low |
| High | High | 0.12 | High |
| Very_High | Very_High | 0.09 | Very_Low |
| Very_High | High | 0.08 | Medium |
| High | Very_High | 0.07 | Extr_High |
| High | High | 0.06 | Extr_Low |
| Extr_High | Very_High | 0.05 | Extr_Low |
| Very_High | High | 0.05 | Low |
| High | High | 0.02 | Extr_High |

Table 7.12: Rules of rule block "RB3"

| IF | | T HEN | |
|---|---|---|---|
| **MECHANIC** | **RIGIDITY** | **DoS** | **MARKUP** |
| Low | Extr_High | 0.66 | Extr_High |
| | Very_High | 0.59 | Very_High |
| Extr_High | | 0.58 | Extr_Low |
| High | High | 0.52 | Extr_Low |
| Very_High | | 0.50 | Very_Low |
| Medium | High | 0.46 | Extr_Low |
| High | Very_High | 0.40 | Extr_Low |
| | Extr_Low | 0.40 | Low |
| | Medium | 0.40 | Medium |
| | Extr_High | 0.40 | Extr_High |
| High | High | 0.22 | High |
| Very_low | | 0.20 | High |
| Medium | | 0.20 | Medium |
| Very_High | Medium | 0.20 | Very_High |
| Medium | Very_High | 0.20 | Extr_High |
| High | Medium | 0.19 | Extr_Low |

| | | | |
|---|---|---|---|
| High | Medium | 0.17 | Extr_High |
| Very_High | High | 0.16 | Very_High |
| Medium | Very_High | 0.16 | High |
| | Very_High | 0.15 | High |
| Medium | High | 0.13 | Extr_High |
| High | Very_High | 0.12 | Very_High |
| Extr_Low | | 0.10 | High |
| Low | | 0.10 | Medium |
| | Low | 0.10 | Low |
| | High | 0.10 | High |
| High | Low | 0.09 | Extr_Low |
| | Extr_High | 0.09 | Very_High |
| Very_High | High | 0.07 | Medium |
| Medium | Medium | 0.05 | Extr_High |
| High | High | 0.05 | Extr_High |
| High | Medium | 0.03 | Medium |
| Medium | High | 0.01 | High |

Table 7.13: Rules of rule block "RB4"

| **IF** | **THEN** | |
|---|---|---|
| **SITEACCE** | **DoS** | **MARKUP** |
| Extr_High | 0.50 | Extr_Low |
| Very_High | 0.48 | Extr_Low |
| Medium | 0.33 | Low |
| Medium | 0.14 | Extr_High |
| High | 0.13 | Very_High |
| Very_High | 0.13 | Extr_High |
| High | 0.12 | Extr_Low |
| High | 0.09 | Extr_High |
| Very_High | 0.06 | Very_High |

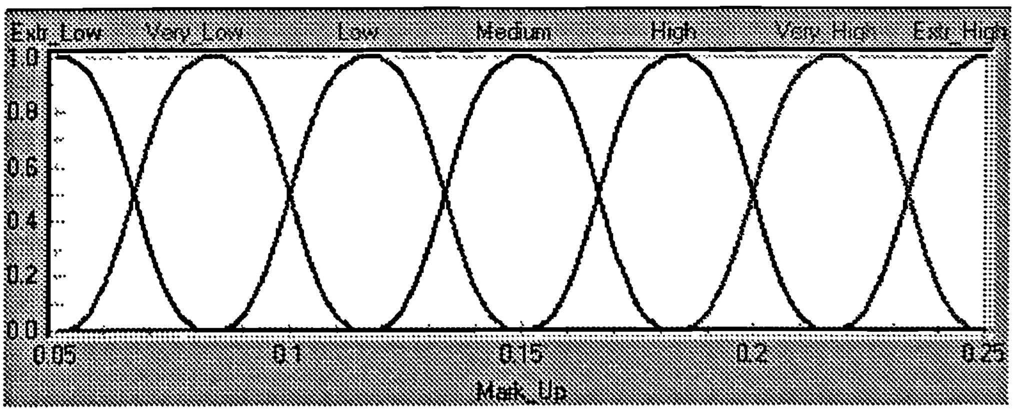



Fig. 7.36: MBF of the output variable "Mark up"

The following section studies how the input variables individually affect the behavior of the developed model.

#### 7.3.1.1 Sensitivity Analysis

The ANN mark up model developed in chapter 6 proved to be very stable and accurate. But the "black-box" feature undermines the confidence in its recommendations. The explicit knowledge representation among additional advantages suggests that the neurofuzzy mark up model might be a better alternative from the ANN model. It is necessary to examine the stability and the accuracy of this model before confirming its superiority. This section studies how changes in individual input variables can affect the model's behaviour. The outputs of the model were recorded while changing the assessment of the first factor (F1) from 0 (extremely low) to 6 (extremely high). Meanwhile, the other factors were set to the mid-point scenario (3 score). The same process was repeated for all the other factors. Table 7.14 shows the outputs computed for different assessments given to each input factor while setting the other factors to the mid-point score.

Table 7.14: Sensitivity of the model output to variation in its inputs.

| Factors | Assessments (Scores) | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | (3) | 4 | 5 | 6 |
| F1 | 0.1398 | 0.1494 | 0.1463 | 0.1773 | 0.1571 | 0.1794 | 0.1925 |
| F2 | 0.1602 | 0.1750 | 0.1583 | 0.1773 | 0.1407 | 0.1411 | 0.1329 |
| F3 | 0.1773 | 0.1773 | 0.1773 | 0.1773 | 0.1773 | 0.1773 | 0.1505 |
| F4 | 0.1883 | 0.1846 | 0.1776 | 0.1773 | 0.1618 | 0.1435 | 0.1336 |
| F5 | 0.1759 | 0.1762 | 0.1755 | 0.1773 | 0.1713 | 0.1623 | 0.1493 |
| F6 | 0.1665 | 0.1755 | 0.1729 | 0.1773 | 0.1590 | 0.1881 | 0.1880 |
| F7 | 0.1827 | 0.1827 | 0.1827 | 0.1773 | 0.1804 | 0.1612 | 0.1537 |

Fig. 7.37 compares between the sensitivity of the neurofuzzy model and the ANN model to changes in their input variables. It can be concluded from Fig. 7.37 that:

1. Extreme values of any input variable does not cause either models to produce unrealistic mark up recommendations;
2. Small changes in most of the input variables might cause larger changes in the output of neurofuzzy model than changes in the ANN model's output; and,
3. Noticeable irregular variations in the neurofuzzy model's output are caused by changes in the following input variables:

- Risks expected (see Fig. 7.37 F1);
- Availability of equipment owned (see Fig. 7.37 F2); and,
- Rigidity of specifications (see Fig. 7.37 F6).

However this irregularity does not form any serious stability problem in the neurofuzzy model. It might be due to some noise in the training data and/or non-linear relationship between the mark up criteria and the mark up size. The ANN model was affected by this noise but also it failed to capture this non-linearity. The following section studies the consistency and the accuracy of the neurofuzzy model.

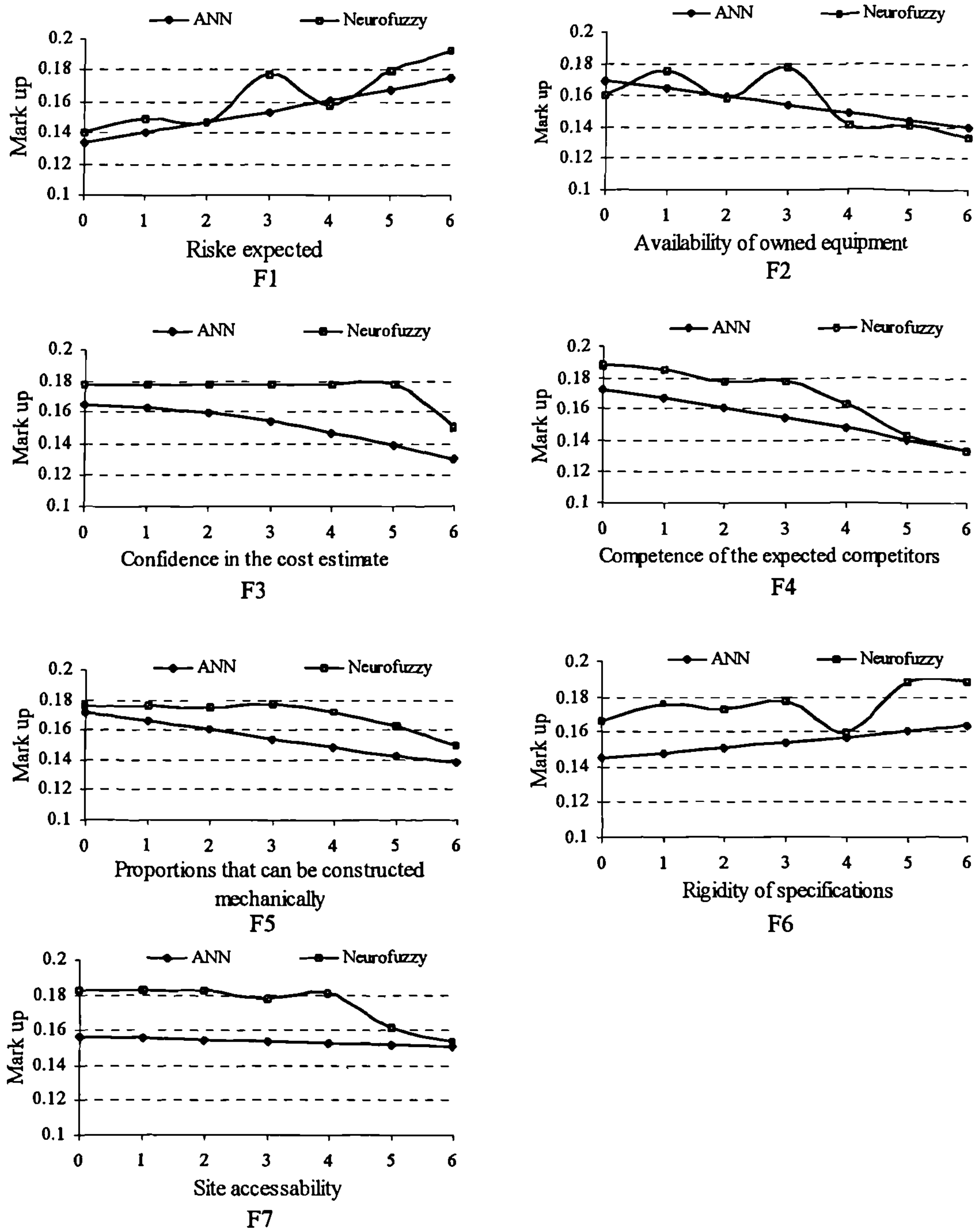



Fig. 7.37: Comparison between the sensitivity of the neurofuzzy and the ANN mark up models to changes in their input variables

#### 7.3.1.2 Testing and Validation

The developed neurofuzzy mark up model proved to be completely consistent as it produced the same output for the same inputs. The accuracy of this model was examined using fifteen real life bidding situations (the same cases used in validating the regression and the ANN models). The contractor's assessments of these situations were presented to the neurofuzzy mark up model, which produced a mark up percentage for each bidding situation. Table 7.15 shows the model recommendation with the actual mark up, error, absolute error, and percentage error for each one of the test cases. The mean error of the model recommendations was very small (ME = 0.0013) and the root mean square error was only (RMS = 0.0126) indicating high reliability of the developed model.

Table 7.15: Actual and predicted mark ups of fifteen real life bidding situations

| Project Number | Actual Mark up | Neurofzzy mark up recommendation | Error | | |
|---|---|---|---|---|---|
| | | | Value | Absolute | (%) |
| 1 | 0.12 | 0.133 | -0.013 | 0.013 | 10.429 |
| 2 | 0.14 | 0.140 | 0.000 | 0.000 | 0.000 |
| 3 | 0.15 | 0.127 | 0.023 | 0.023 | 15.333 |
| 4 | 0.13 | 0.132 | -0.002 | 0.002 | 1.912 |
| 5 | 0.18 | 0.169 | 0.011 | 0.011 | 6.111 |
| 6 | 0.15 | 0.127 | 0.016 | 0.016 | 10.733 |
| 7 | 0.18 | 0.188 | -0.008 | 0.008 | 4.375 |
| 8 | 0.16 | 0.146 | 0.014 | 0.014 | 8.625 |
| 9 | 0.12 | 0.107 | 0.013 | 0.013 | 10.833 |
| 10 | 0.11 | 0.121 | -0.011 | 0.011 | 10.000 |
| 11 | 0.10 | 0.111 | -0.011 | 0.011 | 11.000 |
| 12 | 0.09 | 0.103 | -0.013 | 0.013 | 14.500 |
| 13 | 0.13 | 0.125 | 0.005 | 0.005 | 3.846 |
| 14 | 0.15 | 0.149 | 0.001 | 0.001 | 0.667 |
| 15 | 0.11 | 0.123 | -0.013 | 0.013 | 11.818 |
| Average | | | 0.0013 | 0.011 | 8.32 |
| RMS | | | 0.0126 | | |

Despite the irregularity in the model responses to changes in some of the input variables, the neurofuzzy model has almost the same accuracy as the ANN mark up model. The mean percentage absolute error is 8.32 as shown in Table 7.15. Therefore, it can be concluded that the developed model is (91.68%) accurate in simulating the actual mark ups selected for the validation sample. Fig. 7.38 shows how close the recommended mark ups to the actual ones. The following section summarises the main findings of this chapter.

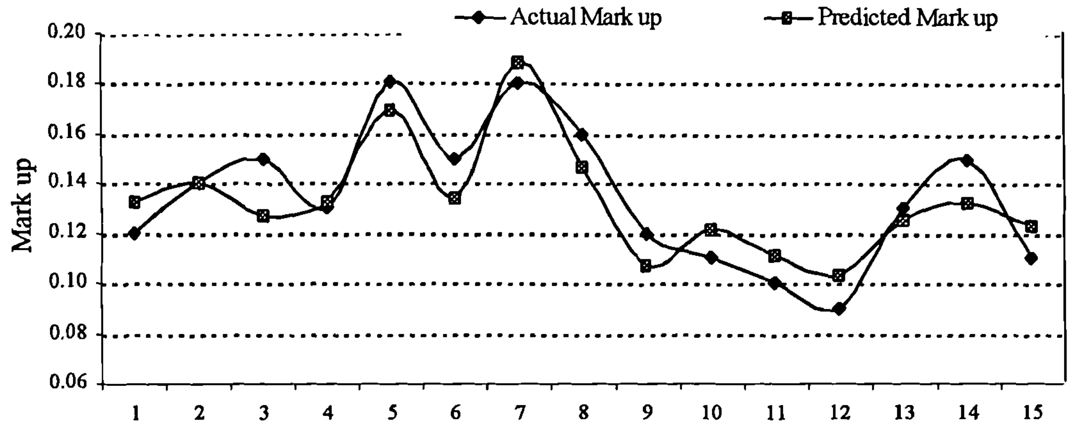



Fig. 7.38: Actual and predicted mark ups of the validation cases

## 7.4 Summary

Attempting to improve the neural network bidding model and to solve its "black-box" problem, the applicability of the neurofuzzy technology on the process of making the bidding decisions was investigated in this chapter. Neurofuzzy is a powerful tool for developing fuzzy and neural network hybrid decision support systems. It combines the explicit knowledge representation and the fuzzy reasoning of the fuzzy logic and the learning power of neural networks. The application of the neurofuzzy technology enabled the development of innovative strategy models that can help contractors in making their bid/no bid and mark up decisions. The same modelling sample and the same input variables that were used in the development of the final ANN bidding model were used in the current chapter to develop neurofuzzy bidding models. A systematic procedure was adopted to examine numerous neurofuzzy models for bot bid/no bid and mark up decisions. The best model was selected for each decision. The sensitivity of the selected models to changes in their inputs was analysed. The results revealed that, although there are some minor irregularity in the models' responses to changes in some input factors, the developed models are robust and consistent. Also, both models generalised solutions for unforeseen bidding situations with high accuracy leading to a conclusion that the neurofuzzy technique is a valuable tool for modelling the bidding process in the construction industry.

# CHAPTER 8
# MODEL SELECTION

## 8.1 Introduction

Several techniques have been used to model the bidding process (see chapters 5-7). This chapter is devoted to summarising the main characteristics and comparing the performance of the generated models to select the most applicable model for each of the "bid/no bid" and mark up decisions. The selection criteria are developed and explained. It has been indisputable that the neurofuzzy approach is the most fitting for both decisions. Thus the neurofuzzy "bid/no bid" and mark up models were combined together and complemented with a simple price model to construct an integrated bidding strategy model called "NET" (a Neurofuzzy Expert system for competitive Tendering in civil engineering). To improve the practicality of the final generated model, it was implemented in a user-friendly prototype.

## 8.2 Development of the Selection Criteria

The selection criteria used to determine which approach is more suitable for each of the bidding decisions are briefly described below (Boussabaine, 1991; Pecar, 1993):

1. **Consistency**: A model is said to be consistent if repeated executions with the same data lead to the same conclusion;
2. **Adaptability**: Adaptability is measured in terms of the model's capability to be customised for particular needs and/or different work environments;
3. **Stability**: The stability, i.e. robustness, of a model is measured by examining its sensitivity to incremental changes in the input space. A model is said to be stable if:
   - Small changes in the input values do not cause large steps in the output;
   - Even extreme input values do not lead to unrealistic conclusions;

4. **User Friendliness**: This is mainly concerned with the quality of the visual interaction between the model and the user. It is a very crucial criterion for winning the acceptance of the end users;
5. **Knowledge Representation**: This refers to how explicitly the knowledge is structured within the model; and,
6. **Accuracy**: Accuracy is measured by comparing the recommendations of the developed models for unforeseen case studies with the actual decisions made in real life for these case studies. Many statistical measurements are usually used for assessing the accuracy of a certain model. These include:
   - ME: The mean error, which is calculated using the following function:

$$ME = \frac{\sum_{i=1}^{N} Ei}{N} \qquad (8.1)$$

   Where:

   $E_i$ is the error, i.e. the difference between the actual ($M_i$)and the predicted result ($R_i$) of project $i$; and,

   N is the number of projects used in the testing process.

   The result from Equation 8.1 shows if the recommendation is systematically biased in either a positive or negative direction. Even in the case of dramatic fluctuations in both directions, the ME could be zero. Thus, it is not enough to be used independently for assessing the accuracy of a model;
   - MAE: Mean absolute error. It represents the magnitude of the despersion from the real values:

$$MAE = \frac{\sum_{i=1}^{N} | Ei |}{N} \qquad (8.2)$$

   - MAPE: Mean absolute percentage error. A very interesting and understandable statistic. It gives an average absolute percentage deviation of the outputs from the actual values.

$$MAPE = \frac{\sum_{i=1}^{N} \frac{| E_i |}{M_i} * 100}{N} \qquad (8.3)$$

However, the MAPE does not take into account positive or negative variations, but rather a typical percentage variation;

- RMS: The root mean square error, which is calculated using the following function:

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} E_i^2}{N}} \qquad (8.5)$$

This statistic is also called a variance or standard deviation (Pecar; 1993) because it measures dispersion although in this case not dispersion from the mean value;

- *Theil*'s U1: A measurement that compares changes in the actual values with the changes taking place with the recommended values (Pecar; 1993). U1 takes value between one and zero. The closer to zero the more accurate the outputs.

$$U1 = \frac{\sqrt{\frac{\sum_{i=N}^{N} E_i^2}{N}}}{(\sqrt{\frac{\sum_{i=1}^{N} M_i^2}{N}} + \sqrt{\frac{\sum_{i=1}^{N} R_i^2}{N}})} \qquad (6)$$

- r: The Pearson correlation coefficient. It is used to indicate how close the recommended outputs to the actual ones. This coefficient is computed by the following formula:

$$r = \sqrt{\frac{\sum_{i=1}^{N} (R_i - M')^2}{\sum_{i=1}^{N} (M_i - M')^2}} \qquad (7)$$

Where M′ is the mean of the actual values.

The value of *(r)* could be anything between -1 and +1. The closer *r* to +1, the more closely the actual values ($M_i$) and the recommended ones ($R_i$) are correlated and thus the more valid the model is. The closer to -1, the more the model has failed to recommend suitable outputs. Also, the closer *r* to zero, the more the model is invalid;

- $R^2$: Determination coefficient. A measurement of how well a model represents the perfect model, i.e. where the same actual results can be predicted. The relationship between the actual and the predicted values can be plotted graphically (see Fig. 8.1). If the model is perfect, the connection points should all be aligned along a straight line at an angle of 45 degrees. In practice, this will never happen. However, the closer the scatter diagram is to this ideal line, i.e. the closer $R^2$ to 1, the better the model is. $R^2$ was produced using the non-linear regression module in the SPSS package.

These criteria are suitable for testing quantitative models. Therefore, they were used to test the mark up models developed in chapters (5, 6, and 7). The mark up models were initially tested using the MAPE parameter. The "bid/no bid" models, being qualitative models, were mainly tested by the percentage of successful recommendations. The following section explains a simple systematic process employed to select the best bidding models.

## 8.3 Model Selection

To systemise the selection process, the aforementioned criteria were used to assess the developed models. The assessment process was carried out by assigning a subjective score between 0 and 10 (low, high) to each selection criterion when considering each model. The total scores gained by a model was considered as its total worth (TW). The model with the highest TW is selected. The following subsection evaluates the general features and the accuracy of the developed " bid/no bid" models to see which one should be selected.

### 8.3.1 The Final "Bid/No Bid" Model

Three models (parametric, neural network, and neurofuzzy) were developed for making the "bid/no bid" decision. Testing these models on real world bidding situations revealed their accuracy and modelling ability. The task in this section is to determine which one of them is the best. The three models were examined in detail considering the selection criteria explained in section 8.2. All models proved to be very consistent as repeated execution with the same inputs always led to exactly the same conclusion. Hence, a "high" score, i.e. 10, was assigned to the consistency criterion for all models. The parametric model can be modified manually by adjusting its parameters ($B_i$, $NB_i$, and $I_i$). No modification can be made by training on new bidding cases. The ANN model can be modified by retraining on new bidding cases but can not be modified manually. Therefore, the parametric and the ANN models were assigned a medium score, i.e. 5, in term of adaptability. On the other hand, the neurofuzzy model can be adjusted more easily by various ways including the following:

- New rules can be added;
- Rules can be deleted;
- Weights, i.e. DS, can be modified;
- Membership functions, premise aggregation and result aggregation methods, and defuzzification methods can be varied; and,
- The model can be trained on new bidding cases that mirror a certain bidding policy.

For these reasons, the adaptability of the neurofuzzy model was assessed as being high (10). The sensitivity of the developed models was tested. No unrealistic conclusions were caused by extreme inputs and no large steps in the output space were caused by small changes in the input space. This problem has been avoided when developing the neurofuzzy model by rejecting the "Mean of Maximum" defuzzification method (MoM) and adopting the CoM method instead although it looked slightly less accurate compared with the MoM (see section 7.2.4). Thus, the stability of all models was considered high and scored "10". Mathematically, the parametric model is very simple and easy to use. However, the user is required to assess the considered bidding situation in terms of relatively large number of factors (nineteen). The ANN and the neurofuzzy models only require assessments of twelve factors. But, the user needs to have some skills in using the development software used. Therefore, the user-friendliness of all models was considered to be medium (5). The knowledge representation (factors, parameters, and indices) in the parametric model is very clear and understandable. Also, it can be viewed graphically (refer to section 5.3.2). Similarly, the knowledge base (the rule base) of the neurofuzzy model leaves nothing unexplained about its behaviour. The knowledge representation of these two models was assessed as "high" (10). On contrary, the ANN model is completely a "black box", which represents the main limitation of the ANN techniques. Thus, a "low" (0) score was assigned to the knowledge representation of the ANN model. The number of successful predictions made by the parametric model is seventeen out of twenty real life bidding situations (85%). The ANN and the neurofuzzy models predicted eighteen out of the same twenty bidding situations (90%). The percentage of the successful prediction was considered as an indication of the accuracy of each model. Table 8.1 summarises the main characteristics of the "bid/no bid" models and the assigned scores in terms of the selection criteria. The sum of all these subjective scores was computed and called the "total worth" index (TW). Fig. 8.1 shows that the Neurofuzzy model has the highest TW.

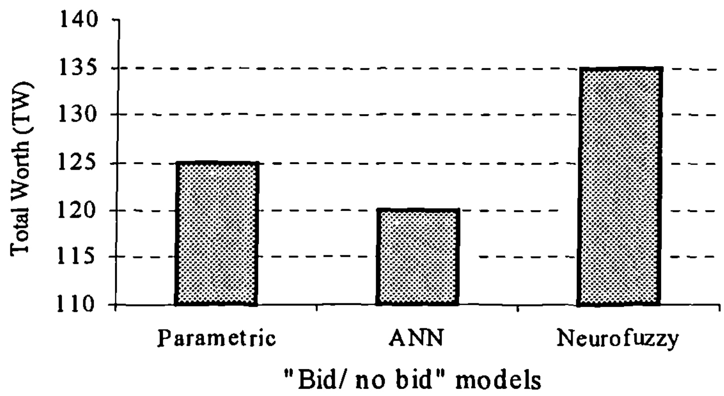



Fig. 8.1: The total worth of the "bid/no bid" models

Hence, it can be concluded that the neurofuzzy model should be selected as the final "bid/no bid" model. The following section follows a similar approach to select the final mark up model.

Table 8.1: Characteristics of the developed "bid/no bid" models

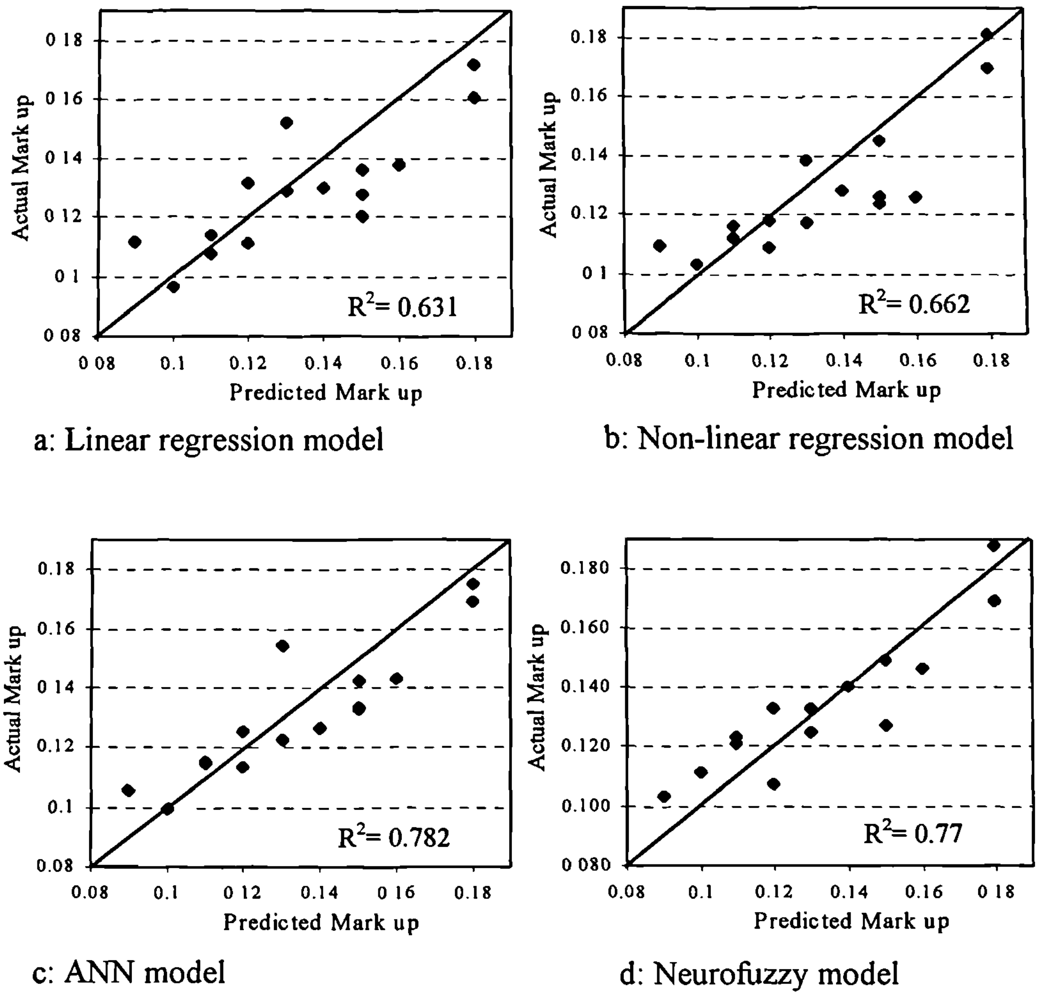
| Selection Criteria | Parametric Model | | ANN Model | | Neurofuzzy Model | |
|---|---|---|---|---|---|---|
| | Description | Score | Description | Score | Description | Score |
| Consistency | Repeated executions with the same inputs lead to the same result | 10 | Repeated executions with the same inputs lead to the same result | 10 | Repeated executions with the same inputs lead to the same result | 10 |
| Adaptability | The parameters (Bi, NBi, and Ii) can be adjusted as required | 5 | The model can be retrained on new case studies to reflect a certain policy | 5 | Almost all components can be modified and the model can be retrained on new cases | 10 |
| Stability | No unrealistic outputs are caused by extreme inputs. No large changes in the outputs are caused by small changes in the inputs. | 10 | No unrealistic outputs are caused by extreme inputs. No large changes in the outputs are caused by small changes in the inputs. | 10 | No unrealistic outputs are caused by extreme inputs. No large changes in the outputs are caused by small changes in the inputs. | 10 |
| User-Friendliness | Nineteen assessments of the considered bidding situation are required | 5 | Skills in using the development software are required. Twelve inputs only. | 5 | Some skills in using the development software are required. Twelve inputs only. | 5 |
| Knowledge Representation | Very explicit | 10 | Very implicit | 0 | Very explicit | 10 |
| Accuracy % | Seventeen successful recommendations out of twenty real life bidding situations. | 85 | Eighteen successful recommendations out of twenty real life bidding situations. | 90 | Eighteen successful recommendations out of twenty real life bidding situations. | 90 |
| | | TW= 125 | | TW= 120 | | TW= 135 |

### 8.3.2 The Final Mark Up Model

The same qualitative criteria used in the previous section to select the best "bid/no bid" model are used in the current section to determine the best mark up model. The quantitative feature of the mark up decision permits employing more detailed statistical measures in the selection process. All the statistical parameters introduced in section 8.2 were computed for all the developed mark up models as shown in Table 8.2.

Table 8.2: Statistical measurements of the accuracy of the mark up models

| Models | ME | MAE | MAPE | RMS | Theil's U1 | r | R squared |
|---|---|---|---|---|---|---|---|
| Linear | 0.0064 | 0.0130 | 0.0993 | 0.0160 | 0.0596 | 0.824 | 0.631 |
| Non-linear | 0.0064 | 0.0120 | 0.0866 | 0.0153 | 0.0570 | 0.850 | 0.662 |
| ANN | 0.0025 | 0.0110 | 0.0793 | 0.0122 | 0.0452 | 0.897 | 0.782 |
| Neurofuzzy | 0.0013 | 0.0110 | 0.0832 | 0.0126 | 0.0462 | 0.881 | 0.773 |




a: Linear regression model

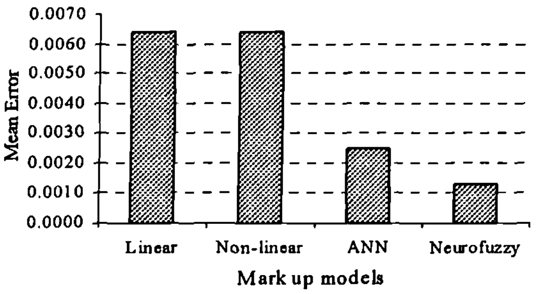
b: Non-linear regression model

c: ANN model

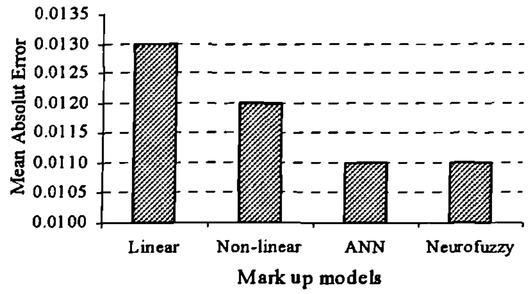
d: Neurofuzzy model

Fig. 8.2: Relations between the mark ups predicted by the developed models and the actual mark ups of the test cases.

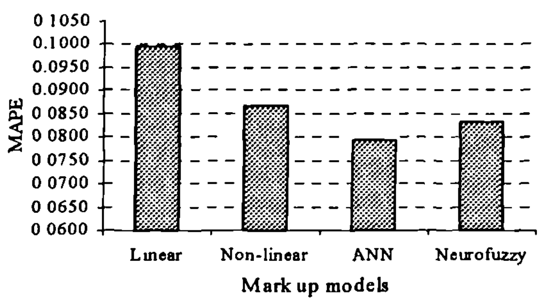
Also, the relation between the actual mark up values of fifteen real life bidding situations and the values predicted by the mark up models is visualised in Fig. 11.2. The determination coefficients indicate how close each model is to the perfect model.



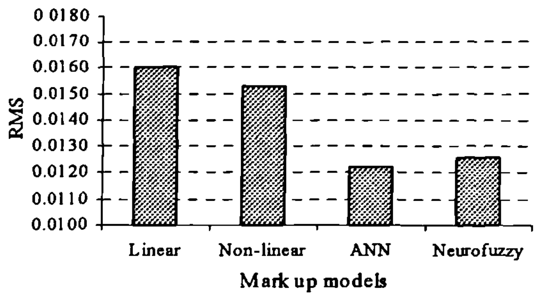
a: The mean error



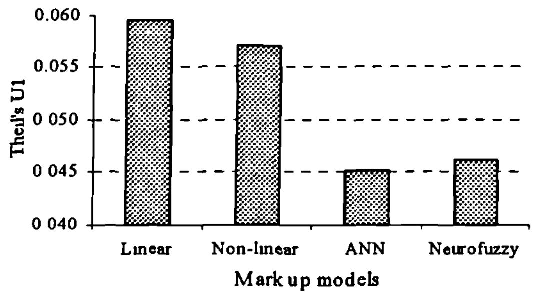
b: The mean absolute error



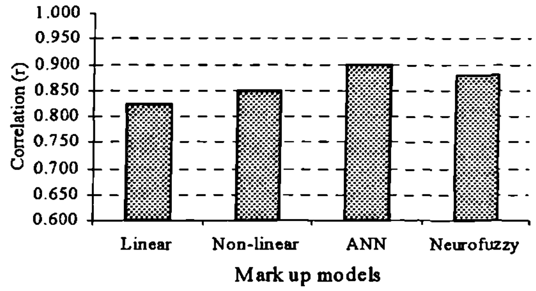
c: The mean absolute percentage error



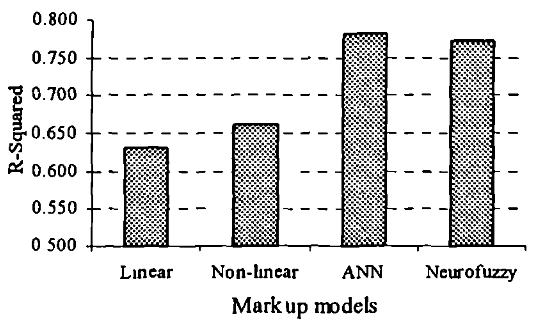
d: The root mean square error



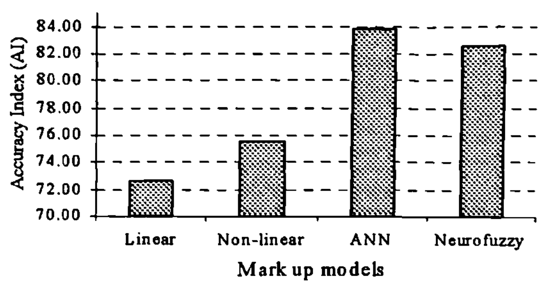
e: The Theil's U1 parameter



f: The correlation coefficient (r)



g: The determination coefficient $R^2$



h: The accuracy index (AI)

Fig.8.3: Error measurements of the mark up models

The neurofuzzy model has the lowest mean error and shares the same lowest mean absolute error with the ANN model as shown in Fig. 8.3 (a) and (b) respectively. The other parameters suggest that the ANN model surpasses the regression models considerably in term of accuracy. But, it is only marginally more accurate than the neurofuzzy model as shown in Figures 8.3 (c, d, e, f, and g). In an attempt to considere all these statistical measurements simultaneously in the selection process, an index called the "accuracy index" (AI) was used. It is computed by the following equation:

$$AI = \frac{R^2 + r - (ME + MAE + MAPE + RMS + U1)}{2} \tag{8.8}$$

This formula was designed in a way that perfect models ,i.e. $R^2$ =100 and r =100 and all the other parameters are zeros, will have an accuracy index of AI =100. However, the exact value of AI does not have any numerical significance. It is used only for comparison proposes. The computed values of AI for the mark up models are shown in Table11.3 and illustrated in Fig.8.3 (h).

Table 8.3: The validation indices of the developed mark up models

| Models | Linear | Non-linear | ANN | Neurofuzzy |
|---|---|---|---|---|
| AI | 72.65 | 75.51 | 83.88 | 82.62 |

The AI values were used as assessments of the "accuracy" selection criterion. The other qualitative criteria were subjectively evaluated in a similar approach to which has been used for the "bid/no bid" models. Table 8.4 summarises the main characteristics and the assigned scores of each mark up model. The total score gained by each model was considered as its total worth (TW). The neurofuzzy model has the highest TW (125.62) compared to the other models as illustrated in Fig. 8.4. Hence, it was selected as the final mark up model.

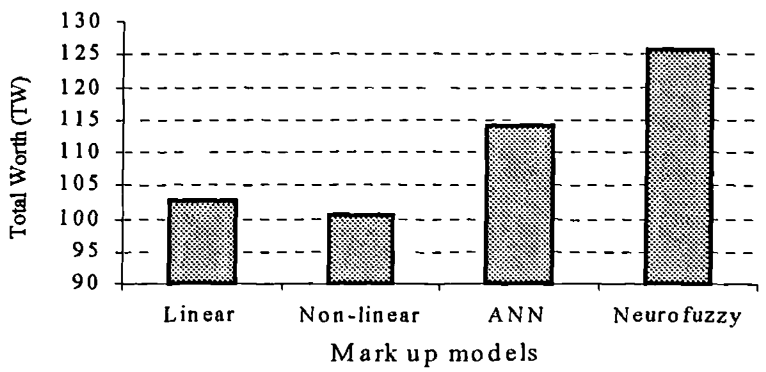



Fig. 8.4: The total worth of the developed mark up models

Table 8.4: Characteristics of the developed Mark up models

| Selection Criteria | | Linear Regression | | Non-linear Regression | | ANN Model | | Neurofuzzy Model | |
|---|---|---|---|---|---|---|---|---|---|
| | | Description | Score | Description | Score | Description | Score | Description | Score |
| Consistency | | Consistent | 10 | Consistent | 10 | Consistent | 10 | Consistent | 10 |
| Adaptability | | Needs to be redeveloped from scratch | 0 | Needs to be redeveloped from scratch | 0 | Can be retrained on new bidding situations | 5 | Can be retrained on new cases and can be modified manually | 10 |
| Stability | | Stable | 10 | Unrealistic outputs can be caused by extreme inputs | 5 | Very Stable | 10 | Stable but there are some unexpected fluctuations | 8 |
| User-Friendliness | | Simple execution of the regression equation. | 5 | Simple execution of the regression equation. | 5 | Skills in using the development software are required | 5 | Some skills in using the development software are required | 5 |
| Knowledge Representation | | The regression equation is known | 5 | The regression equation is known | 5 | Very implicit | 0 | Very explicit | 10 |
| Accuracy | ME | 0.0064 | 72.65 | 0.0064 | 75.51 | 0.0025 | 83.88 | 0.0013 | 82.62 |
| | MAE | 0.0130 | | 0.0120 | | 0.0110 | | 0.0110 | |
| | MAPE | 0.0993 | | 0.0866 | | 0.0793 | | 0.0832 | |
| | RMS | 0.0160 | | 0.0153 | | 0.0122 | | 0.0126 | |
| | U1 | 0.0596 | | 0.0570 | | 0.0452 | | 0.0462 | |
| | r (%) | 82.400 | | 85.000 | | 89.700 | | 88.100 | |
| | $R^2$ (%) | 63.100 | | 66.200 | | 78.200 | | 77.000 | |
| | | | TW= 102.65 | | TW= 100.51 | | TW= 113.88 | | **TW= 125.62** |

The selected "bid/no bid" and mark up models were integrated togather and complemented with a basic price model as will be explained in section 8.4.

### 8.3.3 t-test for Paired Samples

The t-test for Paired Samples was used to check the validity of selecting the meurofuzzy mark up model as the best model. The results of this test came as a strong conformation of the selection process. The differences between the actual mark up values and the results of each mark up model were analysed as shown in Table 8.5 and in Fig. 8.5.

Table 8.5: Comparison between the actual and predicted mark up size

| | Actaul_Linear | | Actaul_Non-linear | | Actaul_ANN | | Actaul_Neurofuzzy | |
|---|---|---|---|---|---|---|---|---|
| **Mean** | 0.135 | 0.129 | 0.135 | 0.128 | 0.135 | 0.131 | 0.135 | 0.133 |
| **Variance** | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.001 |
| **Observations** | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| **Pearson Correlation** | 0.822 | | 0.852 | | 0.897 | | 0.880 | |
| **Hypothesised Mean Difference** | 0 | | 0 | | 0 | | 0 | |
| **Degree of Freedom** | 14 | | 14 | | 14 | | 14 | |
| **t Statistic** | 1.357 | | 1.769 | | 1.053 | | **0.357** | |
| **2-tail Significance** | 0.196 | | 0.099 | | 0.310 | | **0.726** | |

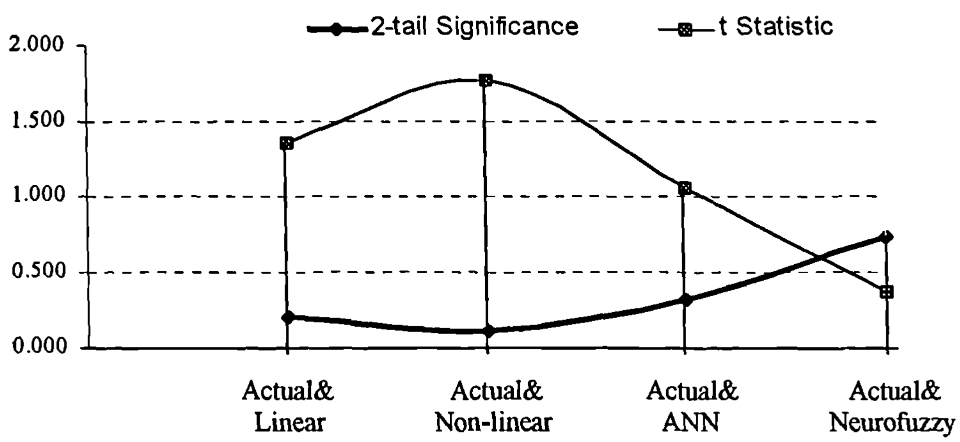



Fig. 8.5: Testing the difference between the actual and predicted mark up

In statistical terms, it can be concluded at a 95% confidence level that all the mark up models are valid and reasonably accurate in predicting the actual mark up size of the test sample. In other word, there is not any significant difference between the actual mark ups and the values predicted by all the mark up models. This conclusion is supported by the relatively high "2-tail Significance" statistic produced when comparing the results of these models with actual values. All of the "2-tail Significance" values are more than (0.05). This conclusion can also be drawn from Fig. 8.6, which illustrates the close relation between the actual mark up of fifteen real life projects and the results of the developed mark up models for the same projects.

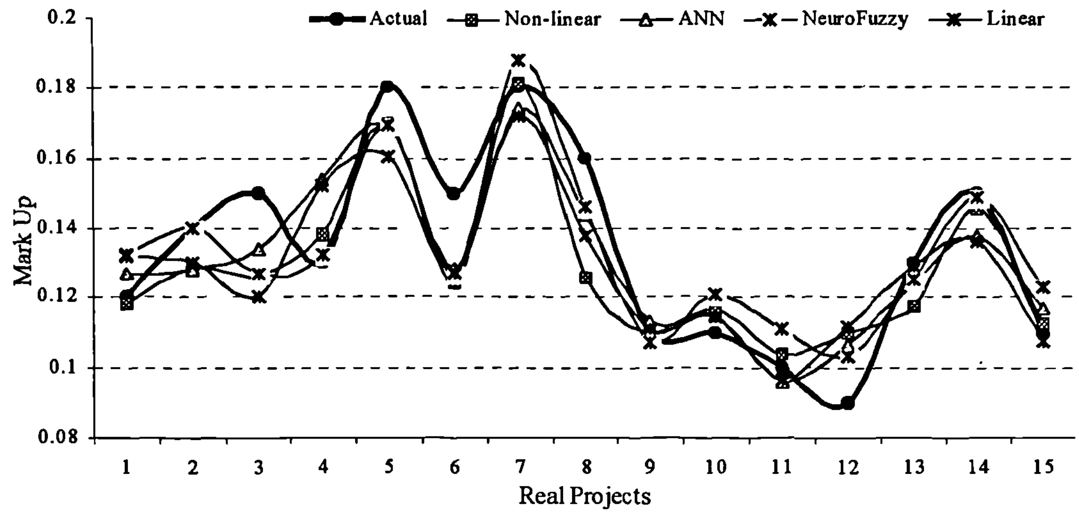



Fig.8.6: Comparison between the mark up models

The neurofuzzy model has the lowest "t" statistic (0.357) and the greatest "2-tail Significance" (0.726) as shown in Fig. 8.5. Hence, one can be more confidant in rejecting the probability of any considerable difference between the actual mark ups and the results of the neurofuzzy model than for the other models. The next more accurate model according to the "t-test" results is the ANN model as shown in the same Figure. Moreover, The neurofuzzy model was compared with the other models using the same statistical approach as summarised in Table 8.6 and shown in Fig. 8.7.

Table 8.6: Comparison between the neurofuzzy and the other mark up models

| | Neurofuzzy-ANN | | Neurofuzzy-Linear | | Neurofuzzy-Nonlinear | |
|---|---|---|---|---|---|---|
| **Mean** | 0.133 | 0.131 | 0.133 | 0.129 | 0.133 | 0.128 |
| **Variance** | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 |
| **Observations** | 15 | 15 | 15 | 15 | 15 | 15 |
| **Pearson Correlation** | 0.908 | | 0.892 | | 0.943 | |
| **Hypothesised Mean Difference** | 0 | | 0 | | 0 | |
| **Degree of Freedom** | 14 | | 14 | | 14 | |
| **t Statistic** | 0.857 | | 1.607 | | 2.723 | |
| **2-tail Significance** | 0.406 | | 0.130 | | 0.016 | |

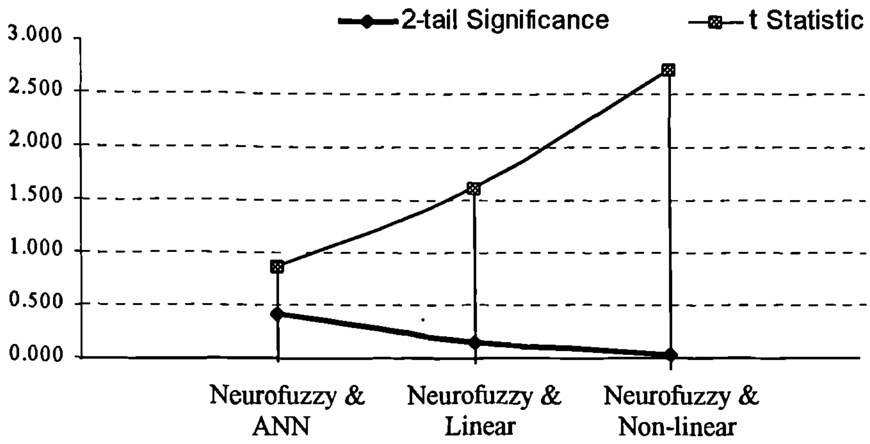



Fig. 8.7: Testing the difference between the mark up models

This comparison revealed that there is not a significant difference between the neurofuzzy model and the ANN and the linear regression models, i.e. 2-tail Significance >(0.05) as shown in Table 8.6. This means that even if one of these two models was the “right” model to be selected, the selection of the neurofuzzy model would not be a serious mistake because they are very similar. Thus, it can be concluded that the neurofuzzy mark up model is the best model in both qualitative and quantitative measures and confidently can be selected as the final mark up model. The selected "bid/no bid" and mark up models were combined together to develop an integrated neurofuzzy bidding strategy model as explained in the following section.

### 8.4 An Integrated Neurofuzzy Bidding Strategy Model

The neurofuzzy "bid/no bid" and mark up models selected in the previous sections were combined to form an integrated bidding model to help contractors in dealing systematically with new bidding situations. Fig. 8.8 shows the flowchart of the integrated model. All a contractor needs is to provide his/her subjective assessment of the considered bidding situation in terms of twelve "bid/no bid" criteria (set S2 in Table 6.2). Then, the model provides a "bid/no bid" recommendation with a certain degree of confidence. Before accepting or rejecting this recommendation, a "what-if" analysis can be performed. This could help the contractor to be more confident in his final decision. If a "bid" decision was made, the contractor is requested to assess the considered bidding situation in terms of another four factors (set S3 in Table 6.13) as three of the mark up factors are shared with the "bid/no bid" decision. Upon these assessments, the neurofuzzy mark up model can provide a mark up recommendation. Also, a what-if analysis can be made before fixing the mark up size. This integrated bidding model was complemented with a basic model for producing the final bid price in the required form (price offer/addition or reduction ratio) and then implemented in a user-friendly prototype as explained in section 8.6. The following section explains the complementary price model.

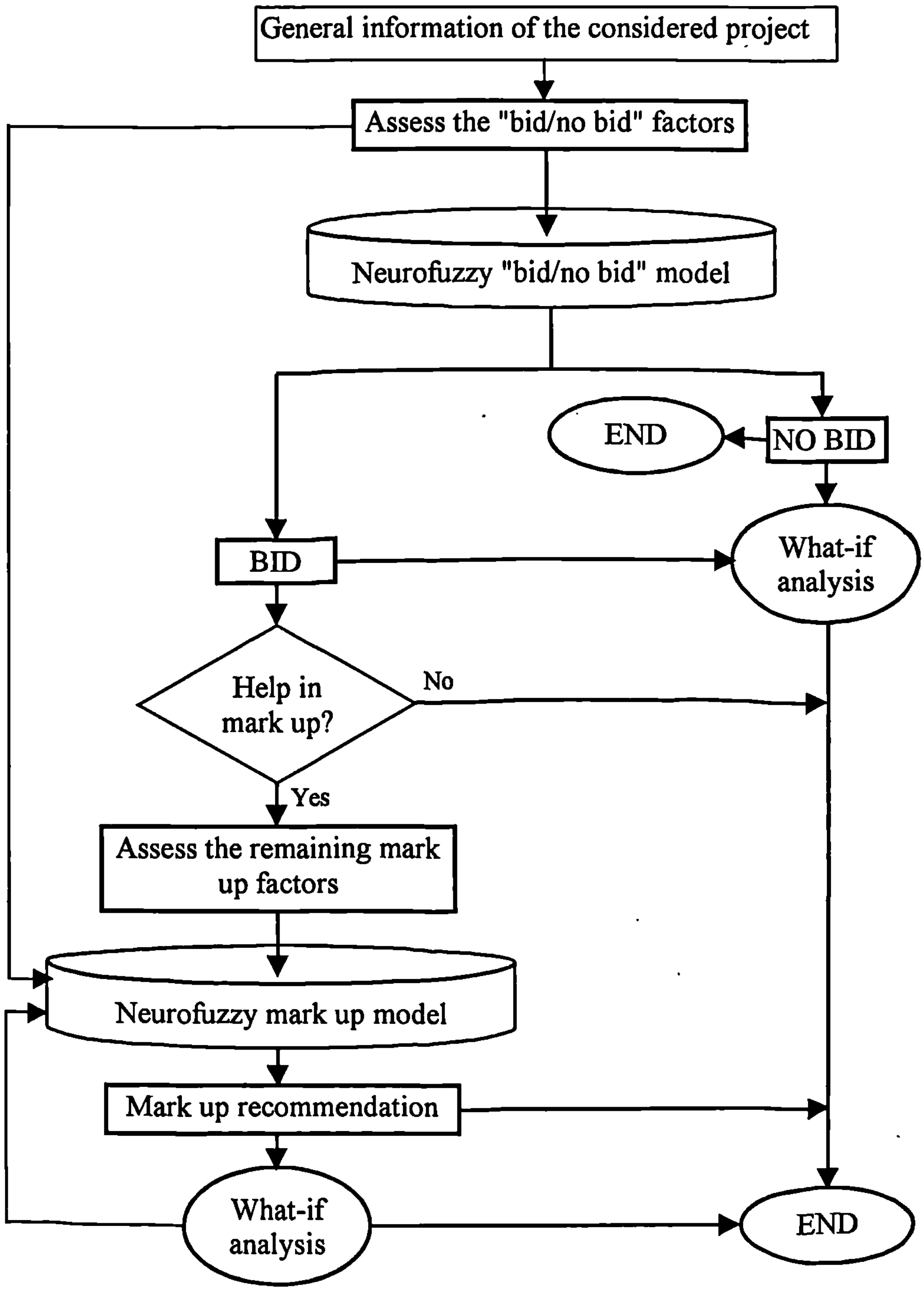



Fig. 8.8: Flowchart of the integrated bidding strategy model

## 8.5 A Model for Producing the Final Bid Price

A simple model was developed to produce the final price ready to be submitted to the client. This model is based on information elicited through semi-structured interviews conducted among Syrian contractors. The interviewees explained how the final tender price is calculated. After it has been decided to submit a bid for a certain project, the cost (direct and indirect) of constructing the project needs to be estimated. Then, a suitable mark up percentage should be selected. Usually, there are two form of the final tender price; a "price offer" or an "addition/reduction ratio" (see section 4.4.1). In the first case, the final tender price is computed using the following formula:

$$P = C^*(1+M) \qquad (8.9)$$

Where:

P: the final tender price;

C: the estimated cost; and,

M: the mark up percentage.

In the case of addition/reduction system, the client provides an approximate cost of the project and invites contractors to submit their offers as a addition or reduction ratios of this approximate cost. The final addition/reduction ratio can be calculated using the following formula:

$$R = \frac{(C * (1 + M)) - C_c}{C_c} \qquad (8.10)$$

Where:

R: is the addition ratio if positive value or the reduction ratio if negative value;

C: the total cost (direct cost + indirect cost) estimated by the contractor;

M: the mark up percentage selected for the project; and,

$C_c$: is the approximate cost estimated by the client.

This simple model is illustrated in Fig. 8.9.

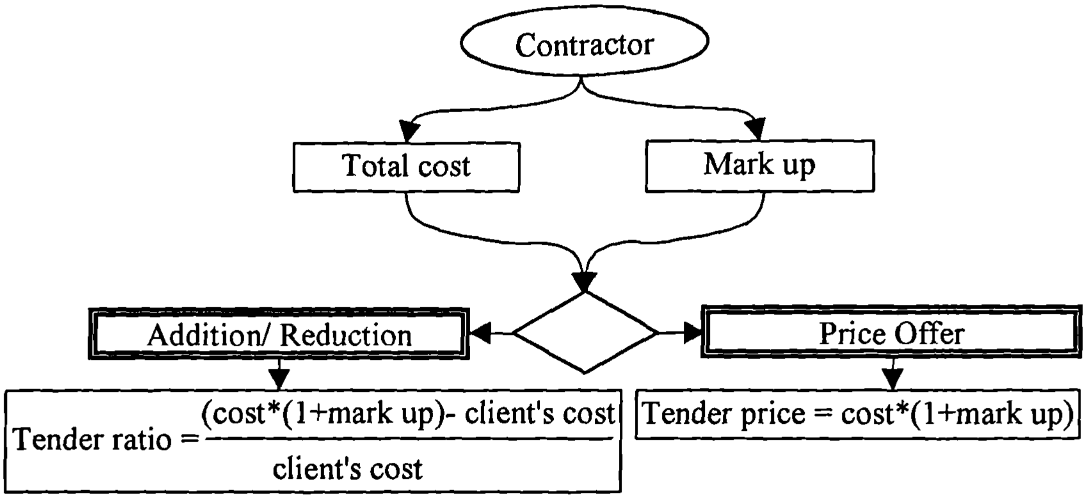



Fig. 8.9: Calculation of the tender price

During the selection process explained in section 8.2, one draw back of the fuzzy logic models was pointed out. This is the complexity of the interaction between the user and the fuzzy logic system. To overcome this problem, the selected fuzzy models were integrated with Microsoft Excel, the visual basic feature of which enables to develop an easy-to-use programmes. This is demonstrated through a real life case study as shown in the following section.

## 8.6 NET: A Neurofuzzy Expert System for Competitive Tendering in Civil Engineering

The final neurofuzzy "bid/no bid" and mark up models are not easy enough to be used by contractors who do not have skills in operating *Fuzzy*TECH software. However, this development software can be integrated with other applications to improve its user-friendliness. These include Microsoft Excel. The input and output variables of the developed fuzzy logic models can be dynamically linked to cells in a normal spreadsheet. When the input variables are changed, the output cells are automatically updated using the fuzzy computation of the integrated fuzzy model. The generated outputs also can be used for further operations within Excel. This facility was exploited to develop a user-friendly spreadsheet prototype called "NET". The application of this prototype is demonstrated by a real life case study (a pipeline project valued at S.P.43,526,000) as follows:

1. First, the user is requested to provide some general information about the considered project. These include the user name, identity of the client, the capital that can be devoted to start the project in the case of winning the contract, approximate project size, date, and project number, name, and duration as shown in Fig. 8.10. The general information of the used case study was interred in this demonstration. If the available capital is less than 20% of the approximate project size, a message is presented automatically to the user recommending not to bid. The user can ignore this message and continue.
2. By clicking on "CONTINUE", the second screen is presented as shown in Fig. 11.11. The user is requested to input his subjective assessment of the bidding situation in terms of twelve bidding criteria by using the scrollbars provided.

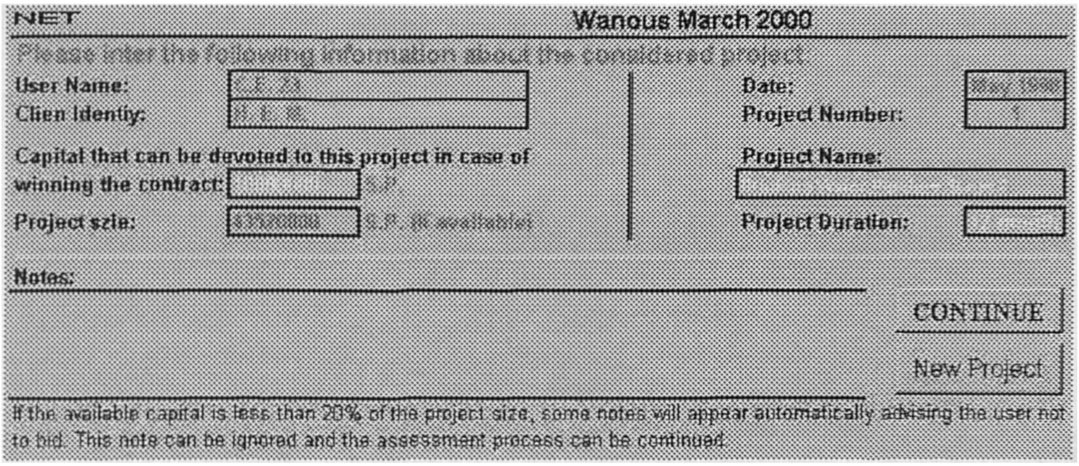



Fig. 8.10: Descriptive project information

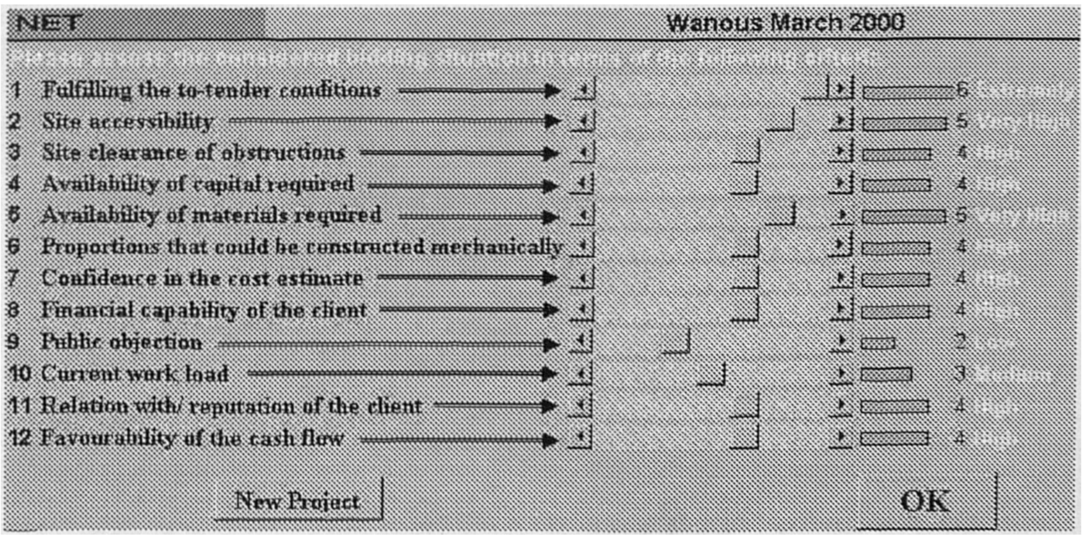



Fig. 8.11: Subjective assessments of the "bid/no bid" criteria

The selected assessments can be viewed graphically, numerically, and linguistically. The real life contractor's assessments of the case study were used. The user has the option to cancel the analysis of the considered project and consider another project by clicking the "New Project" button.

3. By clicking the "OK" button, the dynamic link with the fuzzy logic bid/no bid model is activated and the third screen is presented containing a "bid/no bid" recommendation with a degree of confidence as shown in Fig. 8.12.

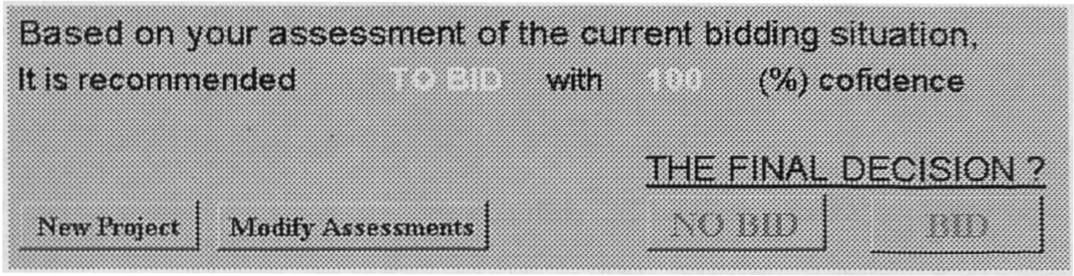



Fig. 8.12: "Bid or No Bid" recommendation

NET recommended "bid" with 100% confidence for the considered case study. This is only a recommendation and the user can select his/her final decision (by clicking NO BID or BID buttons). It is possible to go back and modify the selected assessments. This can be used to perform a what-if analysis before making the final decision.

4. By clicking the "BID" button, the fourth screen is presented asking the user whether help in setting a margin, i.e. mark up percentage, is needed as shown in Fig. 8.13.

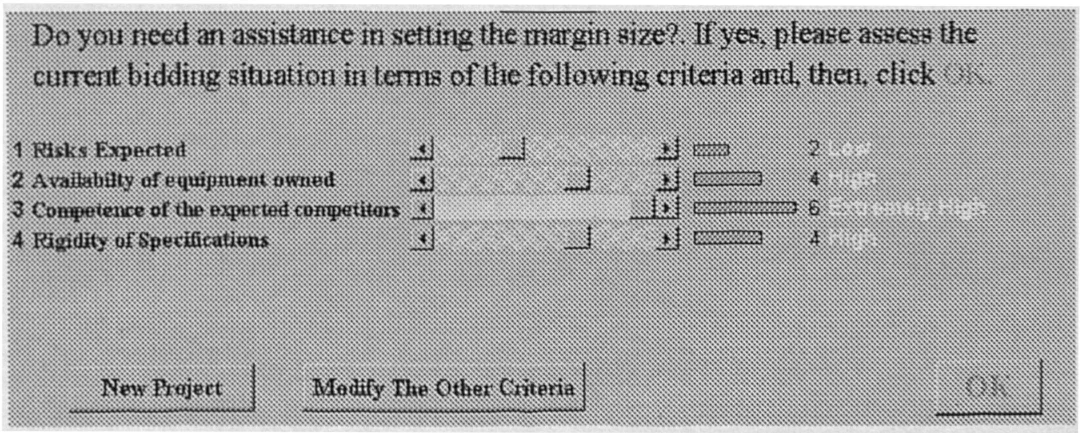



Fig. 8.13: Subjective assessments of the mark up criteria

If help is needed, subjective assessments of four mark up factors are requested. The other three factors (site accessibility, proportions that can be constructed mechanically, and confidence in cost estimate) are shared with the "bid/no bid" decision. The real life assessments of the considered case study were used. Also, a what-if analysis can be made in this stage by modifying the selected assessments.

5. After selection the final assessments, a click on the OK button leads to the fifth screen, which requests the estimated direct and indirect costs of the considered project as shown in Fig. 8.14. These are (S.P. 33124000) and (S.P. 3975000) respectively in the used case study. The user is also requested to input his the approximate project cost estimated by the client if it is available and to select the type of tender adopted. The addition/reduction ration procedure was used in the current bidding situation.
6. A click on the "Addition OR Reduction" button activates the dynamic link with the fuzzy mark up model to select a mark up percentage and presents the results in the final screen as shown in Fig. 8.15. These include the model "bid/no bid" recommendation with its degree of confidence, the final contractor's "bid/no bid" decision, the estimated direct cost, the estimated indirect cost, the total estimated cost, the approximate cost estimated by the client, the recommended mark up, the final tender price, and the addition/reduction ratio.

The model recommended a mark up of 10.7% of the total estimated cost, i.e. 5.65% reduction of the client's estimate. The actual mark up selected in real life was 12% of the total cost estimate, which corresponds to 4.5% reduction ratio. In a case of "price offer" tender, the final output contains all information included in Fig. 8.15 except the addition/reduction ratio and the client estimate because they are not available in such tendering procedure.

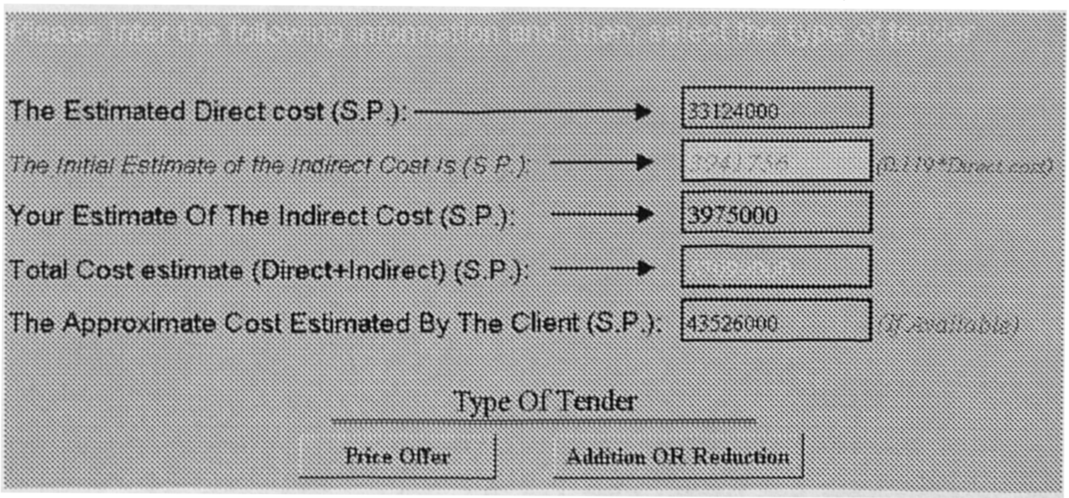



Fig. 8.14: Direct and indirect cost estimation

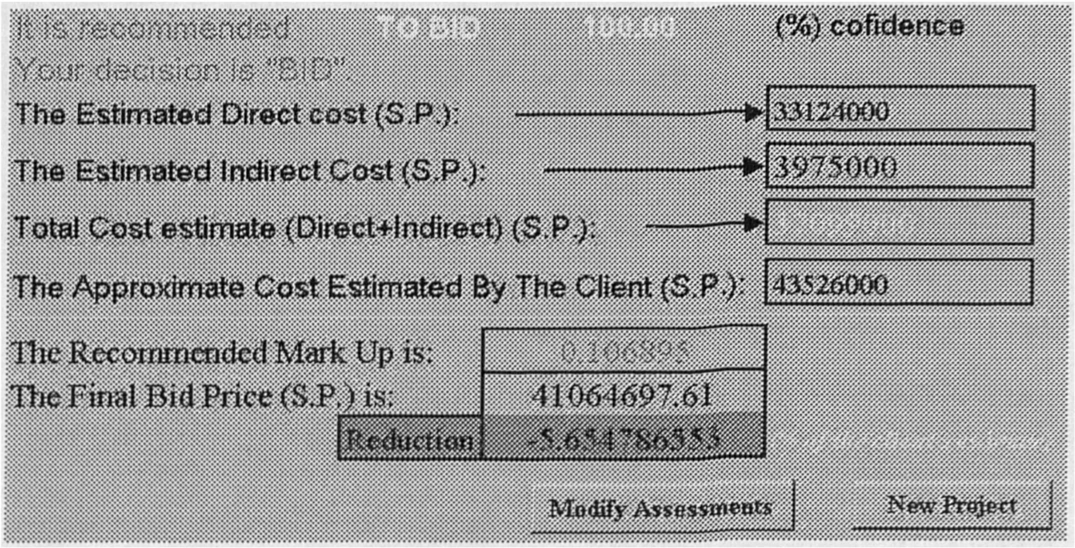



Fig. 8.15: The final output screen

This section demonstrated how the user-friendliness of the selected fuzzy bidding models was improved through implementing them in a spreadsheet prototype.

## 8.7 Summary

The bidding decisions have a strategic importance for any construction company. This motivated a detailed examination of various modelling techniques in an attempt to develop the best possible decision-support system to help in making these decisions. Three parametric ,ANN, and neurofuzzy models were developed for the "bid/ no bid" part of the bidding process. Four linear regression, non-linear regression, ANN, and neurofuzzy models were developed for the mark up selection part of this process. All the developed models proved to have good ability to simulate the actual decisions made in real life bidding situations. The current chapter was devoted to study the performance and the main characteristics of the developed models leading to the selection of the best model for each bidding decision. Qualitative and quantitative selection criteria were used. According to these criteria, the selected model should have the best possible combination of the following features:

1. High consistency;
2. High adaptability;

4. User-friendly;
5. Explicit knowledge representation; and,
6. High accuracy in simulating real life decisions.

The accuracy of the "bid/no bid" models was measured mainly by the percentage of successful predictions made for twenty real life bidding situations. The quantitative nature of the mark up size permitted the use of more detailed statistical error measurements to test the accuracy of the mark up models. As a result, the neurofuzzy models proved to be superior to the other models. The selected neurofuzzy "bid/no bid" and mark up models were combined together and complemented with a simple model for calculating the final bid price. The final integrated model was implementing in a user-friendly spreadsheet prototype called NET (a Neurofuzzy Expert system for competitive Tendering in civil engineering). The application of this prototype was demonstrated using a real life bidding situation. The following chapter discusses briefly the findings of this work and how it relates to previous studies in the field of competitive tendering in the construction industry.

# CHAPTER 9
# DISCUSSION

## 9.1 Introduction

The principal objectives of this study were to uncover the must influential factors that underlie the competitive tendering decisions in the Syrian construction industry, quantify their impact, and develop a means to help contractors in making the strategic bidding decisions. The current chapter is devoted to discussing the main findings of the research presented in this thesis and to put it in the context of previous research in the area of competitive tendering. The discussion will focus on what bidding factors were considered, techniques applied, and the ability to help in making both bid/no bid and mark up decisions.

## 9.2 Factors Affecting the Bidding Decisions

Numerous surveys have been carried out in many countries with the aim of identifying the important factors that affect the bidding decisions in these countries (see section 3.3). The results of these surveys differ due to different aims of the surveys, different bidding conditions, and different factors considered in each country (Odusote and Fellows, 1992). Therefore, to identify the factors that characterise the bidding decisions in Syria, a new survey was required. Based on previous research and on the author's practical experience in the Syrian construction industry, potential bidding factors were identified and included in this new survey. Also, semi-structured interviews were conducted among expert Syrian contractors to explore how they approach the bidding decisions and to explain the tendering procedures used in Syria. Expectedly, analysing the participants' opinions revealed that there is a considerable difference between the bidding factors considered in Syria compared to other countries. Table 9.1 presents the top five important factors that affect the bidding decisions in six countries including Syria. The following subsections highlight the difference between the bid/no bid and the mark up factors and the relative importance assigned to them in these countries.

Table 9.1: The first five important bidding factors considered by contractors in different countries

| Country | Researcher(s) | Bid/no bid decision | Mark up decision |
|---|---|---|---|
| USA | Ahmad and Minkarah 1988 | 1. Type of job<br>2. Need for work<br>3. Identity of the client<br>4. Current workload<br>5. Historic profit | 1. Degree of hazard<br>2. Degree of difficulty<br>3. Uncertainty in cost estimate<br>4. Need for work<br>5. Current workload |
| UK | Shash, 1993 | 1. Need for work<br>2. Number of competitors tendering<br>3. Experience on similar projects<br>4. Current workload<br>5. Client identity | 1. Degree of difficulty<br>2. Risks due to the nature of the work<br>3. Current workload<br>4. Need for work<br>5. Contract conditions |
| Saudi Arabia | Shash & Abdul-Hadi 1992 | Not available | 1. Size of contract<br>2. Availability of required cash<br>3. Type of contract<br>4. Duration<br>5. Uncertainty in cost estimate |
| Australia | Fayek, 1996 | Not available | 1. Desire for project<br>2. Need for work<br>3. Amount of contingency in cost estimate<br>4. Experience on similar projects<br>5. Likelihood of winning contract |
| Canada & USA | Hegazy & Moselhi, 1995 | Not available | 1. Need for work<br>2. Market conditions<br>3. Job complexity<br>4. Job uncertainty<br>5. Firm capability |
| Syria | Wanous, 2000 | 1. Fulfilment of the "to-tender" conditions imposed by the client<br>2. Financial capability of the client<br>3. Reputation of the client<br>4. Project size<br>5. Availability of time for tendering | 1. Risks expected<br>2. Competence of the expected competitors<br>3. Expected degree of competition<br>4. Rigidity of specifications<br>5. Degree of Builability |

### 9.2.1 Bid/No Bid Factors

The "fulfilment of the to-tender conditions imposed by the client" is the most important bid/no bid factor considered by Syrian contractors. The extreme importance of this factor is indicated by its importance index (Ib=90% shown in Table 4.4). The low standard deviation (0.37) indicates a strong agreement between the respondents on this high importance. Also, the interviewed contractors recommended that the "no bid" decision should be made when the fulfilment of the to-tender conditions was not very high, regardless of the other factors. This is expected, as there is no point in submitting a bid that is very likely to be rejected. Contractors in other countries do not need to consider this factor. This due to the difference in the bidding procedures used in these countries. In the Syrian competitive tendering system, a client intending to construct a new project, although he/she usually imposes some conditions, invites all interested contractors to submit their bids for this project. The closed tender is usually adopted in other countries, i.e. only pre-selected contractors are invited to compete on a certain project. In this case, all invited contractors fulfil the "to-tender" conditions, as they are included in the tendering list. The "need for work" and the "current workload" are two important factors in both UK and the USA. These factors are usually highly correlated. Therefore, only the "current workload" factor was considered in the present study. This factor has been assigned less importance in Syria compared to the UK and USA. The client identity is an important factor in all surveyed countries. The availability of owned equipment has little importance when deciding whether or not to bid on a new project in Syria. This is presumably because required equipment can be obtained easily by hire, lease, and sub-contracting. This view is also supported by other researchers including Odusote and Fellows (1992) and Drew and Skitmore (1993). Similarly, although contractors are committed to mobilise new projects depending on their own funds, the availability of capital required was not assigned the expected importance level. This is again because contractors can obtain short loans to cover the initial costs. Primarily, the responsibility for the financial resources is the client's. This explains why the reputation and the financial standing of the client are so important when considering a new project for bidding.

### 9.2.2 Mark up factors

The correlation analysis conducted on the real bidding situations revealed that some factors although they have high importance indices do not have considerable influence on the mark up size in Syria. These factors include:

1. "Current workload", which is very important in other countries such as UK and the USA, indicates the contractor's keenness to win the bid. Despite many attempts to clarify the questions included in the survey and to increase the response rate through telephone calls and/or personal visits, some contractors might get confused between their "current" workload and the workload when they decided about each bid.
2. "Experience on similar projects". This is also an important factor in Australia. However, its effect is accounted for in other factors such as "Confidence in the cost estimate". Contractors can not be highly confident in estimating the cost of a new project without considerable experience on similar ones.
3. "Project size", which is the most influential mark up factor in Saudi Arabia. It is expected that contractors would accept less profit for large projects. Therefore, the correlation between the "project size" factor and the mark up size ($r = -0.021$) was expected to be more significant. On the other hand, large projects imply higher risks and subsequently demand higher mark up to cover them. This might justify the low correlation between the mark up and this factor.
4. "Contract conditions" is an important factor in Saudi Arabia and the UK. Contract conditions are standard for almost all construction projects in Syria. Therefore, it does not represent a major mark up factor for Syrian contractors.

Unlike other countries, "degree of competition" and "competence of expected competitors" are in the top five mark up factors in Syria. Other usually important factors include the "Availability of equipment required". Generally, construction equipment is highly available in Syria compared to the volume of projects being constructed. Therefore, contractors might not need to worry about this factor ($r = 0.005$). However, it is important to distinguish between the availability of equipment in the market and the availability of idle owned equipment, which has considerable effect on the mark up in Syria ($r = -0.636$). Finally, it worth noticing that, although the same factors affect both bidding decisions in Syria, many important factors in one decision have minor influence on the other decision, e.g. “risks expected” and “fulfilment of the to-tender conditions”. Some factors have considerable effect on both decisions, e.g. “availability of materials required”. Some other factors have moderate effect on both decisions, e.g. “project duration”. Researchers have used various but similar methods of analysis to identify the importance of the bidding factors. The following section explains some of these methods.

### 9.2.3 Methods of Analysis

The formal survey conducted by Ahmad and Minkarah (1988a) is probably the first attempt to uncover the factors that construction contractors consider as important in making the bidding decisions. A scale from 1 (not important) to 6 (highly important) was used in this survey. The method used to analyse the responses was based on the percentage of respondents who selected scores of 4 or greater. Thirty one factors were identified and ranked according to the percentage of contractors who assigned a score of 4 or greater to them. A similar method was used by Shash (1993) to assess the importance of 55 bidding factors considered by top UK contractors. The only difference is that the scale used was between 1 and 7 and the cut-off point used was 5 instead of 4. The identified factors were finally ranked according to the weighted average of the contractors' responses. Shash and Abdul-Hadi (1993) used the weighted average method only as an importance index to rank the identified thirty seven factors that affect the mark up size in Saudi Arabia. Hegazy and Moselhi (1995) have considered the relative influence of the mark up factors as a base to rank them. Fayek (1996) used both methods used previously by Ahmad and Minkarah and Shash. Forty six factors were ranked according to the percentage of contractors who assigned a score of 4 or greater and to their importance indices (weighted average of responses). A comparison between the two rankings showed that there is a certain degree of consistency between them. As the method of the weighted average is more commonly used, it was used in the present study.

Due to the existing disagreement among authors as to the factors that are important in making the bid/no bid decision, Odusote and Fellows (1992) reviewed the literature and listed forty two factors identified by 17 other authors. These factors were ranked according to the number of authors who considered them as being important in the process of project selection. The top factors include:

- Identity and reputation of the client (11 authors out of 17);
- Ability of client to pay (10 authors); and,
- Time available in which to tender (8 authors).

These findings are very much in line with the results of the present study regarding the most important bid/no bid factors. Whereas, there is some inconsistency between the findings of Odusote and Fellows and the other sampled studies (see Table 9.1). For example, number of competitors and experience in similar projects are respectively the second and the third factors in the UK according to Shash (1993) but they are in the twenty first and the twenty eighth places according to Odusote and Fellows (1992). The following section compares the final model developed in the present study and previous models in term of the modelling techniques used, showing many significant advantages of the neurofuzzy technique used in this work over previous techniques

### 9.3 Modelling Techniques

Numerous techniques have been used to model the process of making competitive tendering decisions. These techniques include expected monetary value, expected utility value, multi-criteria decision analysis, regression analysis, expert systems, neural networks, and fuzzy set theory. The application of the neurofuzzy technology was investigated in the present study leading to the development of innovative systems for competitive tendering in civil engineering. Table 9.2 shows the main advantages and disadvantages of bidding models developed using different techniques. The majority of bidding models available in the construction literature are based on the expected monetary value or the expected utility value methods.

Table 9.2: Advantages and disadvantages of bidding models based on different modelling techniques

| Modelling techniques | Example | Main Characteristics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Disadvantages | | | Advantages | | | | | | | |
| | | Over simplified assumptions | Historical data required | Mathematical/ statistical knowledge required | Multiple criteria considered | Risk attitude of decision-makers | Subjective assessments | Easy to develop | Easy to use | Easy to interpret results | Bid /no bid | Mark up |
| Expected monetary value | Friedman, 1956 | Yes | Yes | Yes | No | No | No | No | No | No | No | Yes |
| Expected utility value | Benjamin 1969 | Yes | Yes | Yes | No | No | No | No | No | No | No | Yes |
| Regrission analysis | Broemser, 1968 | No | No | No | Yes | Yes | Yes | No (*Non-linear*) | Yes | Yes | No | Yes |
| Multi-criteria decision analysis | Seydel and Olson, 1990 | No | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes | No | Yes |
| Expert systems | AbouRizk et al, 1993 | No | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Neural networks | Hegazy and Moselhi, 1994 | No | No | No | Yes | Yes | Yes | Yes | Yes | No | No | Yes |
| Fuzzy set theory | Fayek, 1996 | No | No | Yes | Yes | Yes | Yes | Yes | No | No | No | Yes |
| **Neurofuzzy** | **Wanous, 2000** | **No** | **No** | **No** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |

These models have been criticised heavily because they are mathematically complex, require historical data that is rarely available about previous projects and expected competitors, and are based on over-simplified assumptions making them unable to represent the real life bidding situations. Due to these limitations, the monetary/utility value models have received little, if any, application in the construction industry as reported by many researchers (Ahmad, 1988a; Shash, 1993, Hegazy and Moselhi, 1995; Fayek, 1996). Bidding models have to meet certain conditions to gain the acceptance of practitioners in the construction industry. These include the following:

1. The user is not required to provide historical data;
2. The user does not need to perform complex mathematical computations;
3. Account for the risk attitude of the decision-maker;
4. Consider other criteria in addition to competition;
5. Accept subjective assessments of bidding situations;
6. Easy to develop;
7. Easy to use; and,
8. Easy to interpret their recommendations (Ahmad, 1988a; Dawood, 1995 and Fayek, 1996).

The traditional statistical models fail to meet any of these requirements. Thus, many attempts have been made to develop more reliable models by applying other techniques. Linear regression analysis was used by Broemser (1968) to develop a mark up model, which provide many advantages over previous models. However, linear regression techniques are not able to model the complex relationships between the mark up factors and the mark up size. On the other hand, development of non-linear regression models is a very time consuming task. The application of multi-criteria decision analysis techniques (e.g. Seydel and Olson, 1990) also succeeded in fulfilling most of the practical requirements. But, the necessity of historical data undermines the application of such models. Recently, expert systems and neural networks techniques have been used to develop bidding strategy models. Most available bidding expert systems (e.g. AbouRizk et al, 1993) still require historical data to be used. Additionally, they are not easy to develop. It is extremely difficult to explain the process of making the bidding decisions in "if-then" rules, which are required for the knowledge base of all expert systems.

Neural networks models (e.g. Hegazy, 1994) provide solutions for most of the limitations of previous models. However, they do not provide any justification of their recommendations, which undermines the user's acceptance of these recommendations. More recently, bidding models were developed using fuzzy set theory (e.g. Fayek, 1996). The main advantage of applying this technique is its ability to handle approximate and fuzzy subjective assessments, which are the bases of making the bidding decisions. However, the development of such models is not easy and potential users need to perform some fuzzy set computations. It can be concluded from Table 9.2 that regression analysis, multi-criteria, and neural networks techniques are more suitable for the development of practical bidding models compared to other methods. Therefore, they were used in the present study to develop bidding models for the Syrian construction industry. The resultant models proved to be accurate in the prediction or actual bidding decisions of real life projects. For more improvement, the application of a new technology (neurofuzzy) was examined. Comparing all the developed models proved that the neurofuzzy technique is more suitable for modelling the bidding process compared to other techniques (see chapter 8). The neurofuzzy model successfully fulfils all the conditions required to win the acceptance of practitioners in the construction industry. It reaps advantages of many techniques; explicit knowledge representation from expert systems, learning power from neural networks, and the ability to handle approximate and fuzzy subjective assessments from fuzzy set theory. Hence, this model is a valuable step forward in the area of competitive tendering. Above these advantages, the developed model is more accurate than previous models. Table 9.3 shows the mean absolute percentage error of the proposed model and previous mark up models, which have been tested on real bidding data.

Table 9.3: Comparison with previous models

| Tendering Strategies | MAPE |
|---|---|
| Hegazy (1994) | 15.11 |
| Li (1996) | 10.00 |
| Fayek (1996) | 11.78 |
| Wanous (2000) | 8.32 |

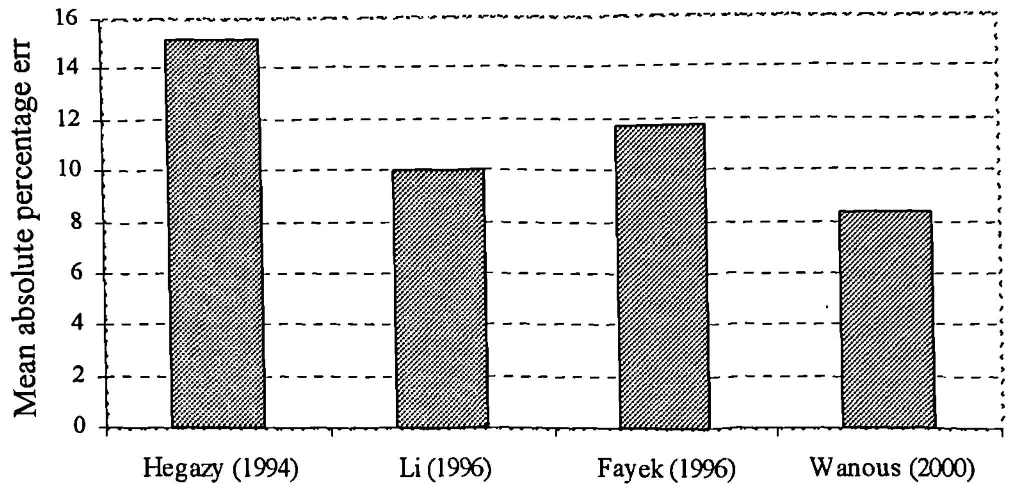



Fig. 9.1: Comparison between the accuracy of NET and previous models

As shown in Table 9.3 and illustrated in Fig. 9.1, the model developed in the present study is more accurate compared to previous models. The errors produced by this model when testing it on real life bidding situations are relatively low as illustrated in Fig. 9.2, which shows the actual mark up values of the test projects.

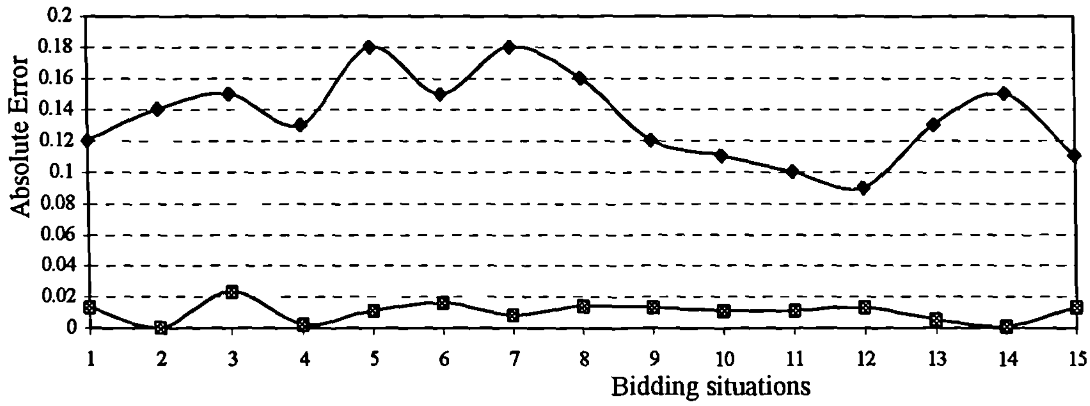



Fig. 9.2: Relationship between actual mark up values and the prediction error

Two important conclusions can be drawn from Fig. 9.2. First, the model is highly accurate in predicting the actual mark up values of the test projects. Second, there is not any clear relationship between the actual values and the prediction error, which means that the model does not produce systematic errors. In addition to its high accuracy, NET is a robust model. Small changes in the input space do not cause large changes in the model's recommendations.

Fig. 9.3 shows the effect of incremental changes in each input variable on the bid/no bid recommendations made by the model (see Table 7.7 and Fig. 7.24).

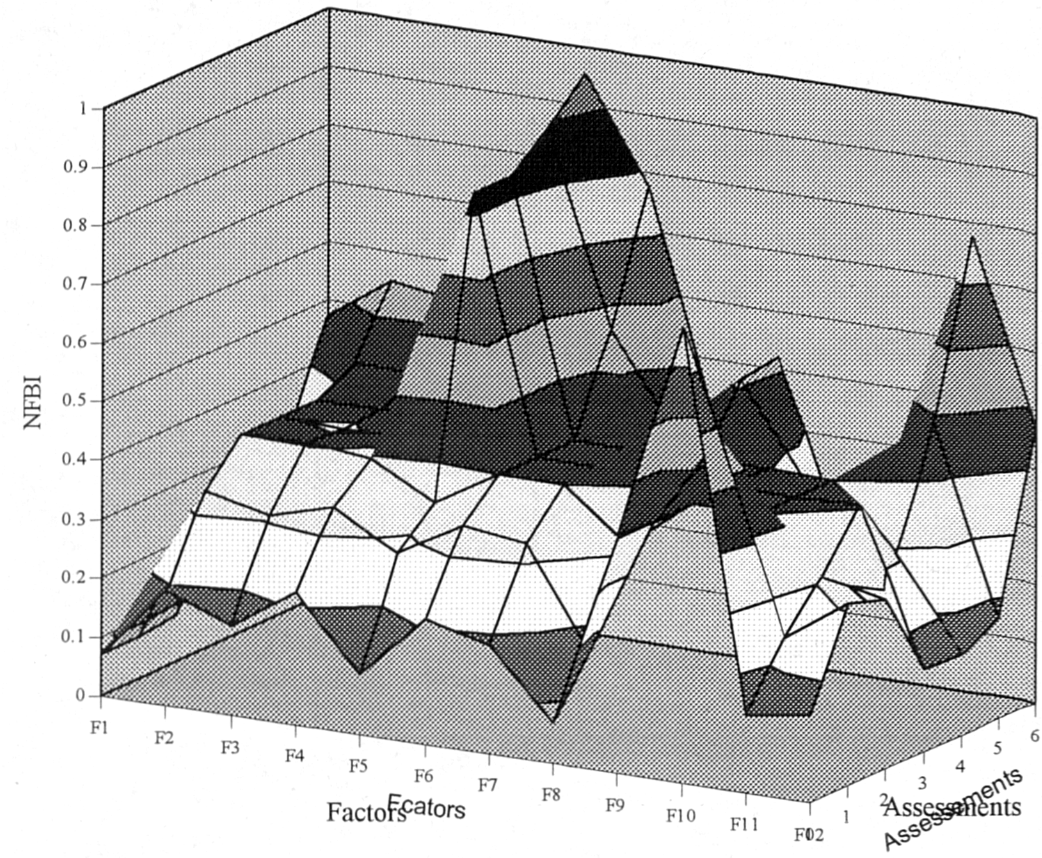



Fig. 9.3: Sensitivity of the neurofuzzy bid/no bid model to changes in its inputs

Despite minor irregularity in the influence of some input variables (see section7.2.8), the bid/no bid part of NET was able to capture important characteristics on the bid/no bid process. These include:

- Fulfilling the to-tender conditions (F1) has a crucial effect on the model's recommendation because it is enough, while the other variable are set to their neutral scores, to cause a "no bid" recommendation unless it is assigned very high scores.
- High current workload (F10) will discourage the "bid" recommendation for new projects; and,
- Good relation with and reputation of a client (F11) generally encourages the "bid" recommendation for projects with him/her.

These characteristics could not be captured by the ANN model (see section 6.4.2.3).

Similarly, Fig 9.4 shows how the mark up part of the developed model would respond to changes in its input variables. Even extreme scores of the input variables would not cause the model to recommend mark up values that are uncommon in real life.

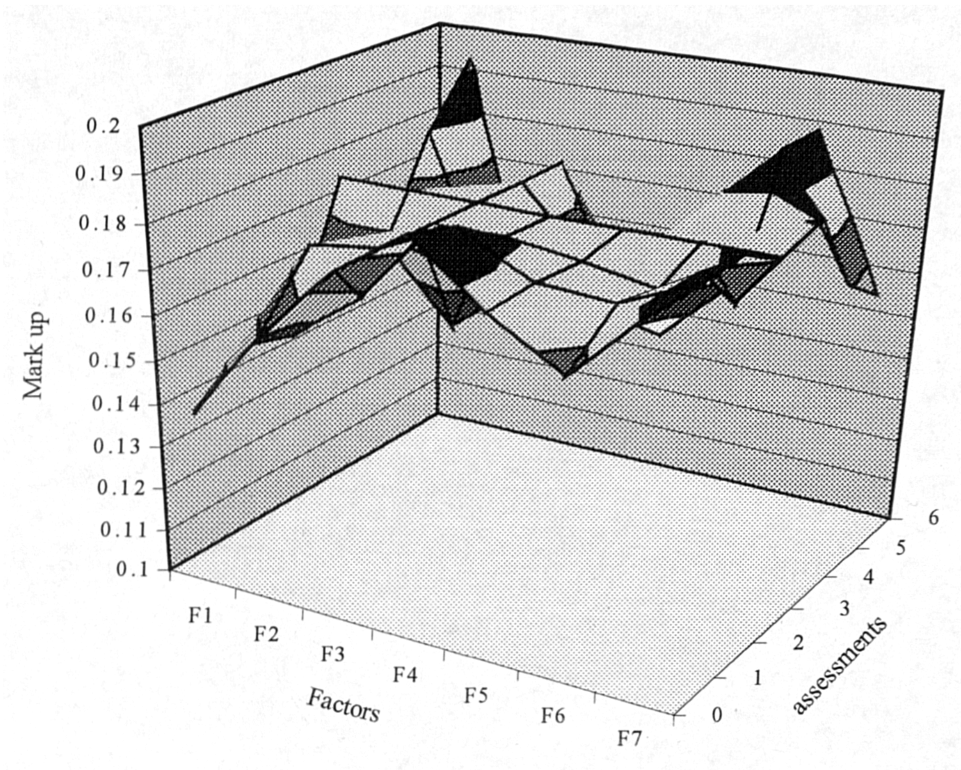



Fig. 9.4: Sensitivity of the neurofuzzy mark up model to changes in its inputs

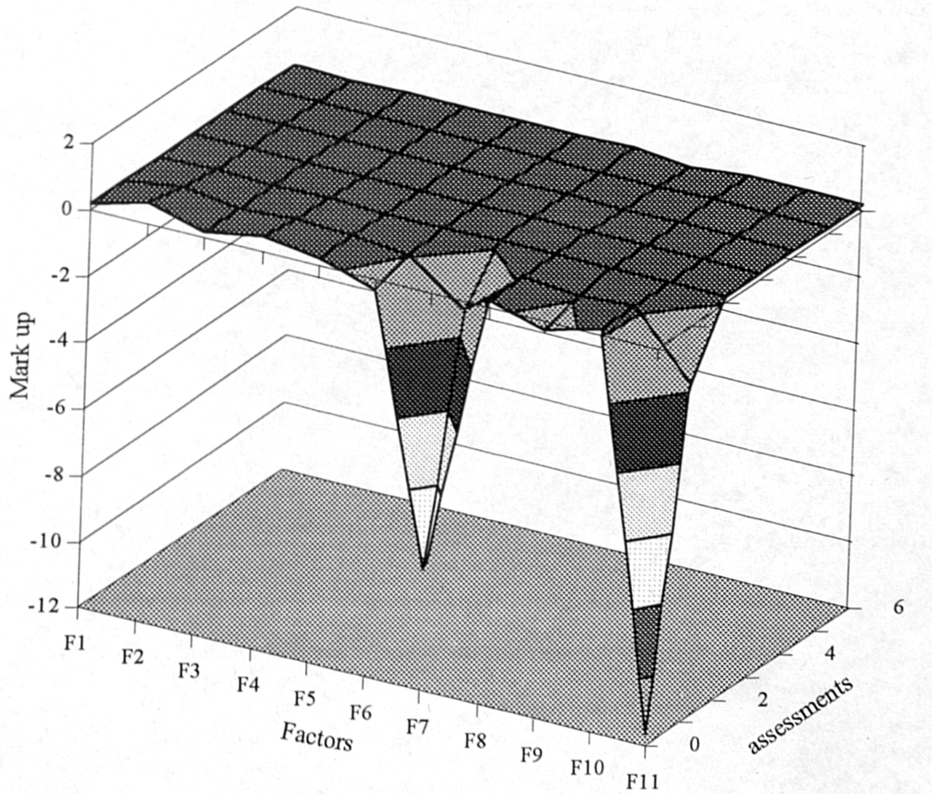



Fig. 9.5: Sensitivity of the non-linear mark up model to changes in its inputs

This demonstrate how the neurofuzzy model provided a good solution for the lack of robustness of the non-linear regression mark up model, which does recommend uncommon mark up values when certain inputs are assigned extreme scores as shown in Fig. 9.5 (see Table 5.12). For example, if the "site accessibility" (F11) was assessed as "extremely low", i.e. 0, the non-linear model would recommend a mark up percentage of (–1164%). Also, the ANN mark up model developed in chapter 6 would not produce such unrealistic recommendations in response to any input values as demonstrated by Fig. 9.6.

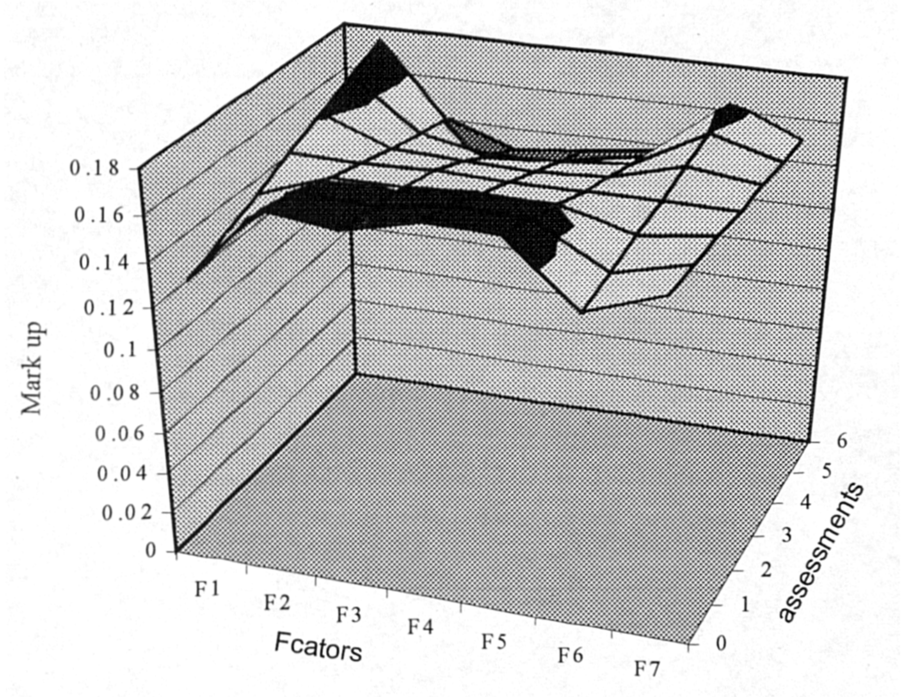



Fig. 9.6: Sensitivity of the neural network mark up model to changes in its inputs

In addition to accuracy and robustness, NET has other advantages over many previous models in term of its scope as discussed in the following section.

### 9.4 Scope

The large majority of previous bidding strategy models are concerned with making the mark up decision. Very few models deal with the first decision (bid/no bid). The neurofuzzy system presented in this study can help in making both decisions based only on subjective assessments of the bidding situation under consideration. The model proposed by Ahmad (1988) provides some assistance to contractors in making the bid/no bid decision. But, it requires a large number of inputs, some of which need considerable experience in dealing with the bidding decisions, making it very hard for new contractors to benefit from this model. The expert system developed by AbouRizk et al (1993) can be of some help in making both bidding decisions. However, this help is very limited because the model is mainly concerned with managing the available resources. It is more accurate to refer to this model as a resources allocation model not as a bidding model. The available resources are not the only criteria affecting the bidding decisions. Another model, which has the ability to help in making both bidding decisions is the expert system developed by Dawood (1995). But it is limited to the precast concrete industry. Almost all remaining models are limited to the mark up decision. Some previous models can aid contractors in cost estimation in addition to the mark up decision (Hegazy, 1993 and Fayek, 1996), which is an advantage of these models over the model presented in this work. However, this model can produce the final bid price in the required format and can be improved to aid in the cost estimation process as suggested in the following chapter.

## 9.5 Conclusion

This study aimed to provide a systematic and qualitative approach to competitive tendering for civil engineering projects in Syria. The Syrian construction industry does not have a formal methodology for making the decisions involved in this process (bid/no bid and mark up). The author's survey revealed that Syrian contractors mostly make the bidding decisions subjectively based on their experienced judgement without any statistical of other formal methods. From previous research, it was concluded that contractors consider bidding factors differently in different countries. Therefore, it has been decided to identify the important factors that affect the bidding decisions in Syria. Using a formal questionnaire survey, supported by semi-structured interviews, thirty five bidding factors were identified and ranked according to their importance to Syrian general contractors. As expected, the importance of the identified bidding factors is different compared to other countries. For example, the "fulfilment of the to-tender conditions" is the top important bid/no bid factor in Syria. But contractors in most other countries do not need to consider it due to the different tendering systems adopted.

In the absence of an agreement among researchers on a suitable modelling technique for the bidding process, the application of many techniques was examined in this study. The neurofuzzy technique proved to be more suitable for the bidding process. It allows the implementation of the bid/no bid and mark up decisions in the same way human experts would make such decisions, that is, never by strict and fixed thresholds, but by intuition and experience. The developed neurofuzzy model is very flexible in the sense that attributes can be changed; rules may be added and others could be deleted, degrees of support could be modified, membership functions could be fine-tuned and so on. Although no model nor the results obtained thereof can claim to be exhaustive or absolutely correct, the bidding model developed in this study provides an effective decision tool for making the bidding decisions. The model has the potential for immediate application to the current bidding practice especially after implementing it in a user-friendly prototype (NET), which does not require the user to perform any mathematical computations or to provide any data on past projects or on potential competitors. All a user needs is his/her subjective approximate assessments of the considered bidding situation in terms of certain criteria. A major conclusion is that neurofuzzy technology can be applied successfully to model both bidding decisions. It is an enhancement on many of previous techniques because it automatically extracts explicit if-then rules by learning from real examples and enables assessments of bidding situations to be made in qualitative and approximate terms, which suits the fuzzy nature of the bidding decisions. Moreover, neurofuzzy technology is a promising development tool that could be used to model other construction engineering and management decisions. The following chapter presents the main contributions and limitations of this work and suggests some possible improvements to overcome these limitations. Also, areas for future research are suggested.

# CHAPTER 10
# SUMMARY AND CONCLUSIONS

## 10.1 Summary

Probabilistic and statistical bidding strategy models were the earliest models developed. The mathematical complexity, the necessity of historical data, and being based on oversimplified assumptions made these models unsuitable for practitioners in the construction industry. However, they are the first attempts to formalise the process of setting the mark up size. Artificial intelligence expert systems and neural network techniques were suggested as suitable tools for developing more reliable and practical models. Considerable improvements were achieved over earlier models in a numbers of ways. These include: incorporating heuristic logic of contractors in dealing with the bidding decisions, mathematical simplicity, some do not require historical projects or data on competitors, and accounting for a greater number of bidding factors in addition to competition.

Despite these important improvements, the developed artificial intelligence bidding models possess a number of limitations. Some expert systems require historical data, which is very unlikely to be available. Most of these models are concerned with only the mark up estimation part of the bidding process neglecting the bid/no bid part, which is at least equally important. Lately, fuzzy set theory was explored and applied on the mark up estimation process with a certain degree of success. The main advantages of the fuzzy set tendering models are their ability to handle approximate and linguistic data. Nevertheless, they require the user to perform some fuzzy set theory mathematical computations.

Therefore, few competitive tendering models are used in practice as reported by numerous publications in the bidding literature. An attempt was made in the present study to overcome some limitations of the previous tendering strategy models. First, the important bidding criteria were identified through a formal questionnaire survey conducted among Syrian general contractors. Some supportive information was collected through semi-structured interviews. Considering the most important bidding criteria, a simple form was designed to elicit data on recent real life bidding situations from the Syrian construction industry. The collected data was analysed and validated against previous studies. The cause-effect relationships between the bidding factors and the actual bidding decisions were studied and the most influential factors were determined. In the absence of a general agreement among researchers that a certain technique is the best for modelling the tendering process, the application of various tools was investigated. Some of these tools have not been applied before on the bidding decisions or in other areas of construction management. Three "bid/ no bid" models and four mark up models were developed and tested. Comparing the performance and the main features of the developed models suggests that the neurofuzzy bidding models are the best and the neurofuzzy technology is more reliable and suitable than the other applied techniques. Thus, the neurofuzzy "bid/no bid" and mark up models were selected and integrated into one bidding strategy model, which can help in making both bidding decisions based on subjective assessments provided by the user. This model has made a number of significant improvements over previous models as pointed out in the following section.

## 10.2 Contributions

The main contribution of the present work is developing and validating an innovative neurofuzzy expert system for competitive tendering in civil engineering called NET. This model is a way of making the bidding decisions by quantifying the subjective evaluations of new bidding situations in terms of certain criteria that have been selected carefully. The presented model has made many advancements over previous models. These include the following:

1. The model can help in making both bid/no bid and mark up decisions;
2. It does not require any historical data on past projects or on competitors;
3. Using the model does not require any mathematical knowledge. All a user needs is his/her subjective, qualitative assessments of the bidding situation under consideration. These assessments can be provided in an approximate numerical form on a scale between 0 and 6 or in a linguistic form such as "low" and "extremely high". This makes the model more suitable for the subjective and fuzzy nature of the bidding decisions;

4. The model is very flexible in the sense that it can be modified very easily to suit other countries or to reflect specific bidding policies. The membership functions can be adjusted, rules can be added and others can be deleted, Degrees of support can be modified manually of by retraining the model on new bidding situations as they are available;
5. NET has the advantages of many techniques. It has the explicit knowledge representation of traditional expert systems, the learning power of neural networks, and the approximate reasoning of fuzzy logic;
6. The model can help in carrying out a "what-if" analysis for one project or screening many new projects and recommending the most suitable one to bid on, which is useful to reduce the bid preparation costs;
7. Although the model is concerned with " bid to win" and "make the maximum profit" objectives, it offers some guidance to achieve other objectives; i.e. "bid not to win" and " work continuity";
8. Through its fuzzy reasoning, NET accounts for the fact that contractors can not be certain in their subjective assessments of a new bidding situation;
9. NET can help contractors in producing the final bid price in the required form, i.e. in a lump sum or an addition/ reduction ratio depending on what procurement system is used. This may increase its practical implementation;
10. The model does not require any assumptions that are necessary to apply probabilistic bidding models;
11. The model retains the ability to consider multiple criteria that affect the bidding decisions, thus it captures more realistically the practice of making the bidding decisions than the probabilistic models based solely of competition and probability of winning the contract with maximum profit; and,
12. The rule base of NET was extracted automatically from real examples, which represents a great improvement over the traditional expert systems the knowledge base of which has to be elicited as "if-then" rules from experts. It is extremely difficult even for highly experienced contractors to explain how they are making the bidding decisions in this form;

Thus, it can be concluded that the presented bidding strategy model (NET) overcomes the main disadvantages of all probabilistic, expert systems, and neural networks previous models. It is also an improvement on models based on fuzzy set theory developed to date, which require some mathematical knowledge on fuzzy sets and are concerned only with the mark up part of the bidding process. Therefore, the model is one of the original contributions made in this thesis to the field of bidding research. The implementation of NET in a user-friendly prototype saves potential users the necessity of having skills in operating the fuzzy logic development software used and makes the model very quick and easy to use and therefore suitable for obtaining rapid decisions. Also, the results of testing NET on real life bidding situations that have not been used in its training, validate its accuracy in simulating the actual bidding decisions and suggest that it could be used in practice as an effective decision-support system with a great degree of confidence. In summary, the developed neurofzzy bidding model fulfils the main objective of this study in developing an integrated qualitative bidding model that:

- Does not require any historical data of past projects or on potential competitors;
- Does not require any mathematical skills;
- Can help in making both "bid/no bid" and mark up decisions;
- Is suitable for the subjective approximate nature of the bidding decisions; and,
- Is easy and quick to use.

Numerous other significant contributions have been made in the current study as summarised in the following section.

## 10.3 Other Contributions

Beside the development of the neurofuzzy bidding strategy model (NET), there are other original contributions of this thesis, which include the following:

1. Identification of the factors that affect the bidding decisions in the Syrian construction industry and ranking them according to their importance level (see sections 4.11 and 4.12);
2. Selection of the most influential bidding factors and studying the cause-effect relationships between them and the actual bidding decisions (bid/no bid and mark up) (see sections 4.16.2, 4.16.3, and 4.16.4);
3. The development of an innovative and easy-to-use parametric model for the bid/no bid process. The results of testing this model on real life bidding situations suggest that it is a valuable approach to systemising the process of making the

bid/no bid decision (see section 5.3). Although this model is based on data from the Syrian construction industry, it provides a universal "shell" that can be applied to other countries, other industries, or other decision-making processes;

4. Although, the regression analysis and neural network techniques have been applied to the mark up selection process by other researchers, the mark up models that are based on these techniques and presented in this work are original contributions since, unlike previous models, they account for some special characteristics of the Syrian construction industry;
5. Some useful progress was made by considering both the importance and correlation with the actual decisions to select potential input variables for the regression models (see section 5.4.1);
6. The algorithm used to select the input variables for the neural network models is a major contribution of this thesis. It considers the correlation between variables and final decisions and different levels of inter-correlation between the variables themselves to form a more systematic selection method than previously available (see sections 6.4.1.1.1 and 6.5.1.1).
7. Another major contribution is the successful application of neural networks technique to the bid/no bid decision-making process. Although numerous applications of this powerful tool have been developed with certain degrees of success in the area of construction management including mark up selection, its suitability for modelling the bid/no bid process has not been investigated previously;
8. In the absence of universal development frameworks for building neural networks and neurofuzzy models, the systematic procedure used to apply these techniques is an important contribution (see sections 6.4.1 and 7.2). This procedure proved to be useful in modelling other processes such as cost estimation and prediction of bankruptcy (see Boussabaine and Wanous, 2000).
9. The reliability of models used to be assessed according to their accuracy. The present work made a significant contribution by considering other criteria. Consistency, adaptability, user-friendliness, knowledge representation, and stability, i.e. robustness, were considered as important issues and an attempt was made to trade them off against accuracy to select the best bid/no bid and mark up models (see sections 8.3.1 and 8.3.2).

In spite of the significant progress made in this work, the developed neurfuzzy expert system suffers from limitations, some of which are highlighted in the following section.

### 10.4 Limitations

No model can claim to be perfect. As such, the final bidding model presented in this study would have limitations, some of which are pointed out as follows:

1. During the analysis of the elicited data, all types of projects (building, pipelines, dams, etc.) were considered together. No analysis was made on the bases of individual types;
2. In its present state, the final system is not flexible enough to enable the user to choose the bidding criteria. However, the pre-selected criteria were obtained based on the questionnaire findings and therefore it would be useful for many users;
3. No consideration is given to the impact of submitting a bid for a new project on ongoing projects and other possible new ones.
4. Inflation has not been accounted for.
5. The developed models are based on specific-population data. The data was collected from the Syrian construction industry.

Further research is needed to overcome such limitations. The following section explores some possible areas of future developments and research.

### 10.5 Recommendations for Further Research

This thesis has identified a number of areas that would benefit from further research. The neurofuzzy expert system developed in this work (NET) could be enhanced in many ways including the following:

1. Considering the impact of different project types. This will require collecting more data on individual project types. The data collected for the present study is not enough to analyse the differences between bidding on different types of projects.

2. Investigating the applicability of the proposed model on other construction industries and making the necessary modifications.
3. Considering different clusters of contractors in terms of experience, specialisation, size, etc.
4. Considering the impact of submitting a bid for a new project on ongoing projects and other possible new projects.
5. Introducing the impact of inflation on the bidding strategy model so it becomes more valid for longer periods.
6. Despite the explicit knowledge representation of the final model, users need to study the rules base to find justifications for the model's recommendations. The model can be considerably enhanced by a direct explanation facility.
7. Adding a cost estimation model. This may increase its practical implementation. As indicated by Anderson and Gaarslev (1996), the narrow scope of the current prototypes is a possible reason for the lack of practical implementation.
8. NET should be expanded to ask for the important information contained in the bulletin of official tenders (BoTs) and to have a data base system for storing a record for each examined project. Such information would be very useful in updating the system.

Three other areas of further research arise from this research. The first area is studying the actual outcomes and the performances of the projects used in this work to develop the bidding models. This could enable determining the bidding decisions that would have been the best for the respective contractors to make. Thereafter, an attempt could be made to develop a new bidding model that can recommend the best decision not only to simulate the practice of the participant contractors as is the case in the developed models.

The second area is to investigate the applications of ANN, regression, and fuzzy logic on estimating the indirect cost of construction projects based on subjective assessments of certain factors. Some of the bidding factors might be influential in this process also.

Using the analysis of the cause-effect relationships between the bid/no bid decision and its criteria (see section 4.16.4) to validate and fine-tune the parametric profiles used in the parametric model, is another area of potential improvement.

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# APPENDIX A

## Questionnaire Survey A

## Decision-Support System for Bidding in Construction

Code:..................
Date: ...... - ...... -1997

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**Dear Mr. ...........................**

It is commonly accepted that the *Bid/ no bid* and *Mark up Size* decisions are relatively complex. This complexity is due to the monetary importance of these decisions and because they are liable to be affected by many internal and external factors.
The main objective of this study, carried out at the University of Liverpool, is to identify these factors and, then develop a computer system that could be used by as a decision support tool for making ***Bid/ no bid*** and ***Mark up*** size decisions.

To develop such a system it is necessary to know how experts, working in the environment of the Syrian construction industry deal with these two decisions. So it would be enormously helpful if you would reply the requests listed in the following pages.

**Thank you very much for your cooperation.**

Yours sincerely

Mohammed Wanous

## *(Part one)*
## *General Information*

1. The typical Type(s) of the projects you deal with (Please tick as appropriate):

◯-Building: → ◯-Housing, ◯-Industrial, ◯-Educational, ◯-Offices
◯-Pipelines: → ◯-Drinking Water pipes, ◯-Waste pipes.
◯-Dams.
◯-Roads. ◯-Others (please specify):..........................

2. The typical size of the projects you deal with (In Sy.P). (Please tick as appropriate):

◯-Less than (10,000,000),
◯-(10,000,000 – 30,000,000),
◯-(30,000,000 – 50,000,000),
◯-(50,000,000 – 70,000,000),
◯-(70,000,000 – 100,000,000),
◯-More than 100,000,000.

3. Minimum capital required to bid for a new project: Percentage of project size, ......... %

4. Current degree of competition. (Please tick as appropriate):

| Very low, | Low, | Medium, | High, | Very high. |
|---|---|---|---|---|
| ◯ | ◯ | ◯ | ◯ | ◯ |

5. Average number of competitors: (Please tick as appropriate)

| 3 or Less | 4-7 | 8-10 | 11 or More |
|---|---|---|---|
| ◯ | ◯ | ◯ | ◯ |

6. Method(s) used in making bid/no bid and mark up decisions:

◯-Statistical/ Mathematical. ◯- Other methods (please specify):..........................
◯-Subjective Judgement. ..........................................................

7-Number of projects tendered for per year: ..................Project(s).

-Number of Project(s) obtained per year: ......................project(s).

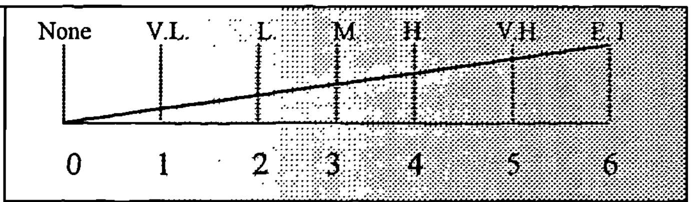
8- Years of experience: ...............*year(s).*

*(Part Two)*

## Factors affecting the "bid/ no bid" and "mark-up size" decisions.

- Please rate the importance of each factor in making **Bid/no bid** and **Mark up size** decisions by circling the appropriate number.

***Where:***
**0**:No importance **1**:Very Low **2**:Low **3**:Medium **4**:High **5**:Very high **6**:Extreme Importance




| Factor Name | Bid/ No Bid | | | | | | | Mark Up | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *- Example ~~~~~~~~~~~~~~~~~~~~~~. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 1- Project Size. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 2- Sufficiency of the original project duration estimated by the client. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 3- Sufficiency of the original price estimated by the client. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 4- Project location. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 5- Availability of time for tendering. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 6- Expected project cash flow. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 7- Degree of buidability . | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 8- Confidence of the cost estimate. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 9- Rigidity of specifications. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |

**0**:No importance **1**:Very low **2**:Low **3**:Medium **4**:High **5**:Very high **6**:Extreme importance

| **Factor Name** | Bid/ No Bid | | | | | | | Mark Up | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10- Risks expected. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 11- Local climate. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 12- Local customs. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 13- Public exposure. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 14- Site accessibility. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 15- Site clearance of obstructions. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 16- Degree of hazard. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 17- Proportions to be subcontracted. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 18- Current work load. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 19- Experience in similar projects. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 20- Relation with and reputation of the owner. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 21- Past profit in similar projects. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 22- Availability of qualified staff. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 23- Availability of labour/ additional supervisory persons required. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 24- Availability of capital required. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 25- Relations with other contractors and suppliers. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 26- The project's geological study. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 | 1 | 2 | 3 | 4 | 5 | 6 |

| 0:No importance 1:Very low 2:Low 3:Medium 4:High 5:Very high 6:Extreme importance | | |
|---|---|---|
| **Factor Name** | Bid/ No Bid | Mark Up |
| 27- Fulfilling the to-tender conditions imposed by the client. | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 28- Availability of materials required. | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 29- Availability of equipment owned by the contractor | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 30- Availability of additional equipment required. | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 31- Fluctuation in labour/ material prices. | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 32- Availability of other projects. | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 33- Expected degree of competition) | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 34- Competence of the expected competitors | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |

- **Please add any missing factors.**

| | | |
|---|---|---|
| 35- | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 36- | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 37- ........................................ ........................................ | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |
| 38- ........................................ ........................................ | 0 1 2 3 4 5 6 | 0 1 2 3 4 5 6 |

## *(Part Three)*

## Practical strategy for making "Bid/ No Bid" decision.

- **Group One:**

Each one of the following factors has been divided into seven levels *(from 0 to 6)*, Which level would you consider being acceptable for **Bidding** (i.e. below that level, the factor will have negative affect on the "bid" decision)? *(Please tick the appropriate circle)*

| |
|---|
| **0**: Extremely Low **1**: Very Low **2**: Low **3**: Medium **4**: High **5**: Very High **6**: Extremely High |

| Factor Name | E.L. 0 | V.L 1 | L. 2 | M. 3 | H. 4 | V.H. 5 | E.H 6 |
|---|---|---|---|---|---|---|---|
| 1-.Sufficiency of the original price estimated by the client's design team. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2- Sufficiency of the original duration. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3- Availability of time for tendering. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4- Confidence in the cost estimate. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5- Favourability of the expected cash flow. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6- Degree of buildability. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7- Suitability of the site climate. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 8- Site accessibility. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 9- Site clearance of obstructions. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 10- Accuracy of the original geological study. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 11- Relation with/ reputation of the client. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| **0**:None, **1**:Very low level, **2**:Low, **3**:Medium level, **4**:High, **5**:Very high level, **6**:Top | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Factor Name** | **None 0** | **V.L. 1** | **L. 2** | **M. 3** | **H. 4** | **V.H. 5** | **Top 6** |
| 12- Experience in similar projects. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 13- Past profit in similar projects. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 14- Availability of qualified staff. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 15- Availability of capital required. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 16- Equipment owned by the contractor. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 17- Availability of equipment required. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 18- Availability of materials required. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 19- Availability of skilled labour. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 21- Financial capability of the client. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 21- Proportions that could be constructed mechanically. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 22- ........................................... | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 23-............................................. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 24-............................................. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**Group Two:** Please tick the maximum acceptable level above which the factor will have negative affect on the "bid" decision.

| **Factor Name** | None 0 | V.L. 1 | L. 2 | M. 3 | H. 4 | V.H 5 | Top 6 |
|---|---|---|---|---|---|---|---|
| 25- Remoteness of the project location. | | | | | | | |
| 26- Contractor responsibility for any unavoidable damages to the local residents' possessions. | | | | | | | |
| 27- Rigidity of specifications. | | | | | | | |
| 28- Laibility of extreme weather. | | | | | | | |
| 29- Degree of hazard | | | | | | | |
| 30-. Adversity of the public exposure. | | | | | | | |
| 31- Probability/effect of risks expected. | | | | | | | |
| 32- Current work load. | | | | | | | |
| 33- Fluctuation in labour/ materials prices. | | | | | | | |
| 34- Expected degree of competition. | | | | | | | |
| 35- Identity/ competence of competitors. | | | | | | | |
| 36- Project size | | | | | | | |
| 37- Availability of other projects | | | | | | | |
| 38- ........................................... | | | | | | | |

- **Thank you very much for your co-operation.**

# APPENDIX B

# Questionnaire Survey B

## University of Liverpool

### General assessment of a new project under consideration

Project Duration: .............. Days | Project Size: ........................... S.P. | Date: ...........-...........-199....

Project Type: - Building - Dams - Pipeline

- Other Projects (Please specify): ..............................................................................

**1- Please assess the project under consideration in terms of the following factors.** (Please tick a score as appropriate).

Example 2 3

| Factors affecting Bid/no bid and mark up | 0% | V. Low | Low | M. | High | V. High | 100% |
|---|---|---|---|---|---|---|---|
| 1- Fulfillment of the to-tender conditions | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 2- Financial capability of the client | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 3- Relation with/reputation of the client | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 4- Project size | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 5- Availability of time to tender | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 6- Avilability of capital required | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 7- Site clearance of obstructions | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 8- Public objection | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 9- Availability of materials required | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 10- Current worklaod | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 11- Experience on similar projects | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 12- Availability of equipment required | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 13- Confidence in the cost estimate | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 14- Availability of skilled labour | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 15- Proportions that could be constructed mechanically | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 16- Sufficiency of the project duration | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 17- Site accessibility | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 18- Risks expected | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 19- Availability of other projects | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 20- Rigidity of specifications | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 21- Availability of equipment owned | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 22- Competence of the expected competitors | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 23- Degree of buildability | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 24- Degree of competition | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 25- Favourability of the expected cash flow | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 26- Remoteness of the project location | 0 | 1 | 2 | 3 | 4 | 5 | 6 |

**2- The final Bid/No Bid decision:**

○ BID ○ NO BID

**3- Tendering procedure used:**

○ Addition/Reduction Ratio

○ Price Offer

○ Other procedures (Please specify): ..............................................................

**4- Project cost estimate:**

| | |
|---|---|
| Direct cost: ....................................S.P. | Final Bid Price<br>................................<br>S.P. |
| Indirect cost: ..................................S.P. | |
| Mark up: ........................................% | |

* <u>Direct Cost:</u> Materials, labour, equipment, subcontractors,...etc.
* <u>Indirect Cost:</u> temporary offices, tax, or any cost not related to specific item.
* <u>Mark up: (gross profit):</u> profit with other allowances.

**5- Bid Result:**

○ - The contract has been won ○ - The contract has not been won

○ - The bid was rejected

**6- Please add any additional remarks.**

..............................................................................................................................................

..............................................................................................................................................

..............................................................................................................................................

***Thank you very much for your co-operation***

## APPENDIX C: NON-LINEAR EQUATIONS

| | |
|---|---|
| $M=0.1051+0.0128*F_1-0.0037*F_1^2+0.009*F_1^3$ | $R^2=0.5682$ |
| $M=0.1739-0.0247*F_2+0.0046*F_2^2-0.0005*F_2^3$ | $R^2=0.4321$ |
| $M=0.2494*EXP(-0.1652*F_3)$ | $R^2=0.4281$ |
| $M=0.5768-0.2544*F_4+0.0496*F_4^2-0.0034*F_4^3$ | $R^2=0.4240$ |
| $M=0.8985-0.4789*F_5+0.1009*F_5^2-0.0072*F_5^3$ | $R^2=0.4200$ |
| $M=0.2512-0.0747*F_6+0.0168*F_6^2-0.0015*F_6^3-0.000021*F_6^4$ | $R^2=0.4050$ |
| $M=0.4906-0.2132*F_7+0.044*F_7^2-0.0033*F_7^3+0.000014*F_7^4-0.000012*F_7^5$ | $R^2=0.3304$ |
| $M=0.1905+0.0222*F_8-0.029*F_8^2+0.0067*F_8^3-0.0005*F_8^4-0.000021*F_8^5$ | $R^2=0.3206$ |
| $M=-0.0214+0.0639*F_9+0.0063*F_9^2-0.0061*F_9^3+0.0007*F_9^4$ | $R^2=0.3204$ |
| $M=0.182*EXP(-0.0962*F_{10})$ | $R^2=0.3060$ |
| $M=0.5233-0.4101*F_5+0.1703*F_{11}^2-0.0318*F_{11}^3+0.0022*F_{11}^4-0.000041*F_{11}^5$ | $R^2=0.2950$ |
| $M= a+b_1*F_1+c_1*F_1^2$ | $R^2=0.4983$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3$ | $R^2=0.5109$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+e_1*F_1^4$ | $R^2=0.5109$ |
| $M= a+b_1*F_1+c_1*F_1^2+e_1*F_1^4$ | $R^2=0.5114$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2$ | $R^2=0.5862$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+c_2*F_2^2$ | $R^2=0.5878$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+c_2*F_2^2$ | $R^2=0.5834$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2$ | $R^2=0.5805$ |
| $M= a+b_1*F_1+c_1*F_1^2+c_2*F_2^2$ | $R^2=0.5761$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+b_3*F_3$ | $R^2=0.6472$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+b_3*F_3+c_3*F_3$ | $R^2=0.6594$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+b_3*EXP(c_2*F_3)$ | $R^2=0.6472$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4$ | $R^2=0.6729$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+b_3*F_3+b_4*F_4$ | $R^2=0.6692$ |
| $M= a+b_1*F_1+c_1*F_1^2+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+c_4*F_4$ | $R^2=0.6695$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+c_4*F_4$ | $R^2=0.7005$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*EXP(c_4*F_4)$ | $R^2=0.6692$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5$ | $R^2=0.6789$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5$ | $R^2=0.6852$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5+d_5*F_5$ | $R^2=0.6854$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+d_5*F_5$ | $R^2=0.6847$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5+d_5*F_5+e_5*F_5$ | $R^2=0.6856$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5+d_5*F_5+b_6*F_6$ | $R^2=0.6859$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5+d_5*F_5+c_6*F_6$ | $R^2=0.6856$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5+d_5*F_5+b_6*F_6+c_6*F_6$ | $R^2=0.6890$ |
| $M= a+b_1*F_1+c_1*F_1^2+d_1*F_1^3+b_2*F_2+b_3*F_3+c_3*F_3+b_4*F_4+b_5*F_5+c_5*F_5+d_5*F_5+b_6*F_6+b_7*F_7$ | $R^2=0.6918$ |

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ b_3*F_3+c_3*F_3+b_4* F_4+ b_5* F_5 + c_5* F_5+ d_5* F_5+ b_6* F_6+ b_7* F_7 + c_7* F_7 \qquad R^2=0.6926$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ b_3*F_3+c_3*F_3+b_4* F_4+ b_5* F_5 + c_5* F_5+ d_5* F_5+ b_6* F_6+ b_7* F_7 + c_7* F_7+ b_8* F_8 \qquad R^2=0.6955$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+ f_1* F_1^5+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ f_5* F_5^5+ b_6* F_6+ b_7* F_7+ b_8* F_8+ b_8* F_8 \qquad R^2=0.6985$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+ f_1* F_1^5+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ f_5* F_5^5+ b_6* F_6+ b_7* F_7+ b_8* F_8+ b_9* F_9 \qquad R^2=0.6985$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+ f_1* F_1^5+b_2*F_2+ c_2* F_2^2+ b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ b_7* F_7+ b_8* F_8+ b_9* F_9 \qquad R^2=0.6832$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ b_7* F_7+b_8* F_8+ b_9* F_9 \qquad R^2=0.6982$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ b_7* F_7+b_8* F_8+ b_9* F_9+ c_9* F_9 \qquad R^2=0.7144$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ b_7* F_7+b_8* F_8+ b_9* F_9+ c_9* F_9^2+ d_9* F_9^3 \qquad R^2=0.7154$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ b_7* F_7+b_8* F_8+c_8* F_8^2+ b_9* F_9+ c_9* F_9^2 \qquad R^2=0.7145$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ b_7* F_7+ c_7* F_7^2+b_8* F_8+c_8* F_8^2+ b_9* F_9+c_9* F_9^2 \qquad R^2=0.7145$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ b_7* F_7+ c_7* F_7^2+b_8* F_8+ c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7163$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ c_7* F_7^2+b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7252$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ d_6* F_6^3+ b_7* F_7+ c_7* F_7^2+ b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7162$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5*F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ c_7* F_7^2+b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7225$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+b_5*F_5+ c_5* F_5^2+ d_5*F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ c_7* F_7^2+b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7057$$

$$M= a +b_1*F_1+ c_1* F_1^2+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ c_7* F_7^2+b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7225$$

$$M= a +b_1*F_1+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ c_7* F_7^2+b_8* F_8+c_8* F_8^2+b_9* F_9+ c_9* F_9^2 \qquad R^2=0.7143$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7204$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+ b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7259$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+ b_3*EXP( c_3* F_3^2)+b_5*F_5+c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7362$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+ b_3*EXP( c_3* F_3^2)+b_5*F_5+c_5* F_5^2+ d_5* F_5^3+ e_5* F_5^4+ b_6* F_6+ c_6* F_6^2+ d_6* F_6^3+ b_7* F_7+b_8* F_8+c_8* F_8^2+b_9* F_9+c_9* F_9^2 \qquad R^2=0.7362$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+ f_1* F_1^5+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3 +b_3*EXP(c_2* F_3) +b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+b_6*F_6+ c_6* F_6^2 + b_7*F_7+ c_7* F_7^2+b_8*F_8+ c_8* F_8^2+b_9*F_9+c_9* F_9^2 \qquad R^2=0.7458$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+ f_1* F_1^5+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3 +b_3*EXP(c_2* F_3) +b_5*F_5+ c_5* F_5^2+d_5* F_5^3+b_6*F_6+ c_6* F_6^2+ b_7*F_7+ c_7* F_7^2+b_8*F_8+ c_8* F_8^2+b_9*F_9+ c_9* F_9^2+ b_{10}*EXP(c_{10}* F_{10}) \qquad R^2=0.7542$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+ e_1* F_1^4+ f_1* F_1^5+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3 +b_3*EXP(c_2* F_3) +b_4*EXP(c_4* F_4)+b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+b_6*F_6+ c_6* F_6^2+b_7*F_7+ c_7* F_7^2+b_8*F_8+ c_8* F_8^2+b_9*F_9+ c_9* F_9^2+b_{10}*EXP(c_{10}* F_{10})+b_{11}*F_{11}+ c_{11}* F_{11}^2 \qquad R^2=0.7684$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3 \qquad R^2=0.6127$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_2* F_2^3+ b_3*EXP(c_2* F_3) \qquad R^2=0.6768$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_1* F_1^3+ b_3*EXP(c_2* F_3)\ \ b_4*F_4+ c_4* F_4^2+ d_4* F_4^3 \qquad R^2=0.7013$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_1* F_1^3+ b_3*EXP(c_2* F_3)\ \ b_4*F_4+ c_4* F_4^2+ d_4* F_4^3+ b_5*F_5+ c_5* F_5^2+ d_5* F_5^3 \qquad R^2=0.7198$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_1* F_1^3+ b_3*EXP(c_2* F_3)\ \ b_4*F_4+ c_4* F_4^2+ d_4* F_4^3+ b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ b_6*F_6+ c_6* F_6^2+ d_6* F_6^3+ e_6* F_6^4 \qquad R^2=0.7270$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_1* F_1^3+ b_3*EXP(c_2* F_3)\ \ b_4*F_4+ c_4* F_4^2+ d_4* F_4^3+ b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ b_6*F_6+ c_6* F_6^2+ d_6* F_6^3+ e_6* F_6^4+b_7*F_7+ c_7* F_7^2+ d_7* F_7^3+ e_7* F_7^4+ f_7* F_7^5 \qquad R^2=0.7490$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_1* F_1^3+ b_3*EXP(c_2* F_3)\ \ b_4*F_4+ c_4* F_4^2+ d_4* F_4^3+ b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ b_6*F_6+ c_6* F_6^2+ d_6* F_6^3+ e_6* F_6^4+b_7*F_7+ c_7* F_7^2+ d_7* F_7^3+ e_7* F_7^4+ f_7* F_7^5+b_8*F_8+ c_8* F_8^2+ d_8* F_8^3+ e_8* F_8^4+ f_8* F_8^5 \qquad R^2=0.7572$$

$$M= a +b_1*F_1+ c_1* F_1^2+ d_1* F_1^3+b_2*F_2+ c_2* F_2^2+ d_1* F_1^3+ b_3*EXP(c_2* F_3)\ \ b_4*F_4+ c_4* F_4^2+ d_4* F_4^3+ b_5*F_5+ c_5* F_5^2+ d_5* F_5^3+ b_6*F_6+ c_6* F_6^2+ d_6* F_6^3+ e_6* F_6^4+b_7*F_7+ c_7* F_7^2+ d_7* F_7^3+ e_7* F_7^4+ f_7* F_7^5+b_8*F_8+ c_8* F_8^2+ d_8* F_8^3+ e_8* F_8^4+ f_8* F_8^5+b_9*F_9+$$

$c_9 * F_9^2 + d_9 * F_9^3 + e_9 *$ $R^2$=0.7753

$$M = a + b_1*F_1 + c_1*F_1^2 + d_1*F_1^3 + b_2*F_2 + c_2*F_2^2 + d_1*F_1^3 + b_3*EXP(c_2*F_3)\ b_4*F_4 + c_4*F_4^2 + d_4*F_4^3 + b_5*F_5 + c_5*F_5^2 + d_5*F_5^3 + b_6*F_6 + c_6*F_6^2 + d_6*F_6^3 + e_6*F_6^4 + b_7*F_7 + c_7*F_7^2 + d_7*F_7^3 + e_7*F_7^4 + f_7*F_7^5 + b_8*F_8 + c_8*F_8^2 + d_8*F_8^3 + e_8*F_8^4 + f_8*F_8^5 + b_9*F_9 + c_9*F_9^2 + d_9*F_9^3 + e_9*F_9^4 + b_{10}*EXP(c_{10}*F_{10})$$ $R^2$=0.7879

$$M = a + b_1*F_1 + c_1*F_1^2 + d_1*F_1^3 + b_2*F_2 + c_2*F_2^2 + d_1*F_1^3 + b_3*EXP(c_2*F_3)\ b_4*F_4 + c_4*F_4^2 + d_4*F_4^3 + b_5*F_5 + c_5*F_5^2 + d_5*F_5^3 + b_6*F_6 + c_6*F_6^2 + d_6*F_6^3 + e_6*F_6^4 + b_7*F_7 + c_7*F_7^2 + d_7*F_7^3 + e_7*F_7^4 + f_7*F_7^5 + b_8*F_8 + c_8*F_8^2 + d_8*F_8^3 + e_8*F_8^4 + f_8*F_8^5 + b_9*F_9 + c_9*F_9^2 + d_9*F_9^3 + e_9*F_9^4 + b_{10}*EXP(c_{10}*F_{10}) + b_{11}*F_{11} + c_{11}*F_{11}^2 + d_{11}*F_{11}^3 + e_{11}*F_{11}^4 + f_{11}*F_{11}^5$$ $R^2$=0.8175

**The final equation:**

Mark up = -9.441112279-0.00628225* $F_1$+0.003808863* $F_1$^2-0.000284558* $F_1$^3-0.288816319* $F_2$+0.06137285* $F_2$^2-0.004294553* $F_2$^3-0.002802286*EXP(0.419293361* $F_3$)-0.165006062* $F_4$ +0.03508057* $F_4$^2-0.002483252* $F_4$^3-0.011653475* $F_5$+0.00396265* $F_5$^2-0.000437456* $F_5$^3+0.510946414* $F_6$-0.186452872* $F_6$^2+0.029107653* $F_6$^3-0.001653161* $F_6$^4+12.377261191* $F_7$-6.887296762* $F_7$^2+1.846476669* $F_7$^3-0.23931915* $F_7$^4+0.012030553* $F_7$^5-0.094035992* $F_8$+0.109280611* $F_8$^2-0.05144907* $F_8$^3+0.010500718* $F_8$^4-0.000774616* $F_8$^5+0.509122872* $F_9$-0.199398855* $F_9$^2+0.032903452* $F_9$^3-0.001948869* $F_9$^4-10.98309836*EXP(0.000259526* $F_{10}$)+17.130708662* $F_{11}$ -9.522532569* $F_{11}$ ^2+2.548534709* $F_{11}$ ^3-0.32951393* $F_{11}$ ^4+0.016513874* $F_{11}$ ^5

# APPENDIX D
# CONCEPTS USED IN DEVELOPING THE ANN BIDDING MODELS

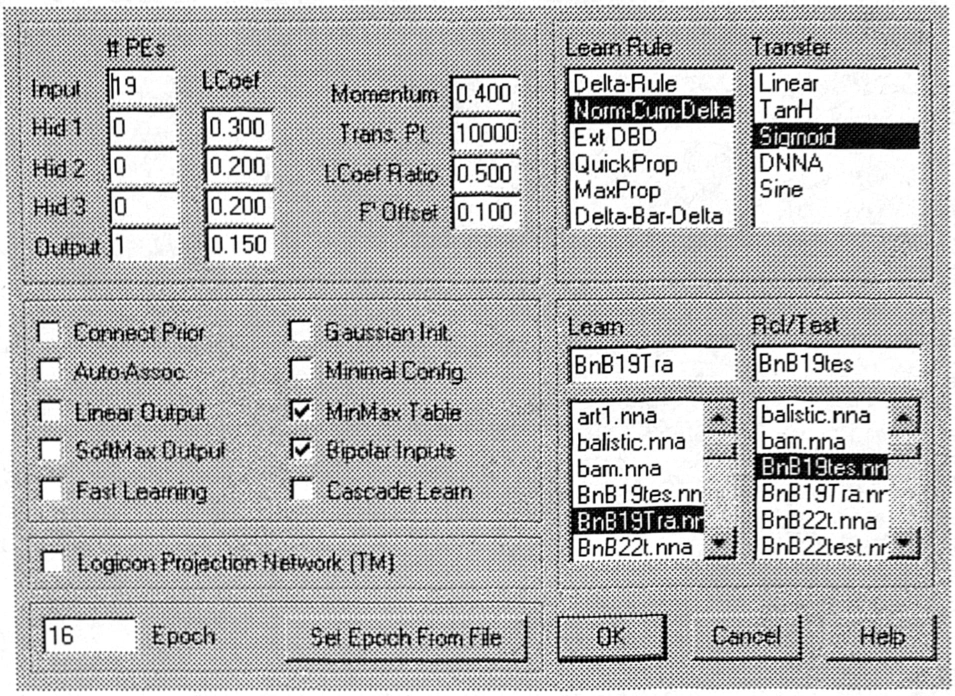



Fig. D.1: Parameters of the initial ANN "bid/no bid" model

The main parameters included in Fig. D.1 are explained briefly as follows (Neural computing handbook 1996) :

1. Learning Coefficients (LCoef):

The (LCoef)s are the initial learning coefficients for each hidden layer and for the output layer. These values set the learning/recall schedules and directly relate to the learning rule. This option can be skipped when using one of the following learning rules: Delta-Bar-Delta, Extended Delta-Bar-Delta, QuickProp or MaxProp because they pre-form learning schedules.

2. Transition Point:

Trans. Pt. is the learn count at which the LCoef is reduced from the initial LCoef by an amount corresponding to LCoef Ratio. At each Trans. Pt. the LCoef is dropped by an amount corresponding to LCoef Ratio. Trans Pts. in the schedule are heuristically set to 3, 7, and 15 times the first Trans. Pt. so that the intervals between Trans. Pts. increase exponentially.

For example, if LCoef =0.5, Trans. Pt =10000, and LCoef Ratio = 0.5, The resulting schedule is:

| Learn coefficient | until Learn Count |
|---|---|
| 0.5 | 10,000 |
| 0.25 | 30,000 |
| 0.0625 | 70,000 |
| 0.00391 | 150,000 |
| 0.00002 | thereafter |

To set a constant learning coefficient, the (Trans. Pt.) is set to 999999.

3. LCoef Ratio:

The LCoef ratio and Trans. Pt. values configure a decaying learn schedule that works in conjunction with the initial LCoef. To set a constant learning coefficient, the LCoef ratio can be set to 1.

4. F' Offset

The F' Offset is the value added to the derivative of the transfer function prior to calculating the value to back propagate from each processing element (PE). For a Sigmoid or TanH transfer function a F' Offset value of 0.1 prevents network saturation.

5. Connect Prior:

This option creates connections from all previous layers. Neural networks are typically built with weights connecting the input and hidden layer, and more weights connecting the hidden and output layer. The "Connect Prior" option adds "jump" connections into a network, creating additional weights connecting the input layer to the output layer. Connections from the input to output layer can be helpful in some networks. These connections effectively deal with aspects of a problem that are not highly non-linear. They bypass the hidden layer and the hidden layer's non-linear transfer function, allowing nearly linear parts of the problem to be solved in a more direct and more linear way.

If only limited data are available for training a network, adding additional processing elements or connections can create a network which is larger than it needs to be.

If too many connections exist and few data points are available, then overtraining (memorisation or overfitting) can occur and the network will be unable to generalise correctly.

6. Auto-Associative:

This option sets the number of output PEs to the number of input PEs and uses the input vector as the desired output. One application of the "Auto-Associative networks is to compress and decompress data. For example, the network may start with 20 of inputs, compress the data into a hidden layer of 10 PEs, and then restore to the same 20 outputs. In this case the data are encoded and contained in the hidden layer states of the network. This encoding can be considered as a method of compressing data. If the number of the PEs in the hidden layer are more than the number of inputs, the data are decompressed in the hidden layer. Connections that jump over the hidden layer would not be helpful in this scenario.

7. Linear Output:

On the output layer, this option overrides the selected transfer function and forces a linear transfer function for the output layer.

8. SoftMax Output:

Forces a linear transfer function and a SoftMax output function, which is usually used for classification type problems in which the desired output is categorical in nature, and the components of each desired output vector add up to 1.

9. Fast Learning:

This option forces Delta-Rule learning and uses Tariq Samad's fast learning variation (Samad 1988).

10. Gaussian Initialisation (Gaussian Init.):

Uses a Gaussian distribution rather than a uniform distribution for initialisation and noise generation.

11. Minimal Configuration (Minimal Config.):

Provides the minimum number of weight fields required for a learning rule. For instance, the minimal configuration of the Norm-Cum-Delta is two weight fields per connection. One to store the weight and the other to accumulate weight changes. If momentum is required, another weight field is added. This option can is helpful is situations of very large networks and limited memory.

12. MinMax Table:

Causes Professional II/PLUS to compute the low and high values for each data field in the selected data I/O file and stores these values in a "MinMax Table", which is explained in the following section.

13. Bipolar Inputs

The raw input values, i.e. original real-world measurements, may have values that are too large or too small. The "Bipolar Inputs" maps the raw input values to fall with in a desired range (-1,+1). Such range may help to keep the network nodes from saturation, i.e. being unable to learn. Similarly, the network may perform better when output values are within a certain range. Network whose activation function is of a sigmoid shape, will perform better if the desired output values are between 0 and 1, e.g. 0.20 - 0.80. Inputs and outputs ranges are used by NeuralWorks software in conjunction with the IO file and the MinMax Table to transform, i.e. scale, the training and testing data to fall within the desired ranges prior to presenting the data to the network. This scaling mechanism is explained in the following section. The desired ranges for the input and output values were set using the "I/O Parameters" dialogue box, which is shown in Fig. D.2. After a network learns on the scaled data, the output needs to be "re-scaled" into the original unites.

14. Cascade Learn

Activates Run/Cascade Learn which implements a form of "Cascade-Correlation Training" algorithm in which hidden layer PEs are incrementally added and individually trained to take responsibility for any remaining output error. Each hidden unit receives input from both the input buffer and from all prior hidden PEs. The number of hidden layer PEs provides a pool of PEs that the "Cascade Learning" algorithm activates one by one until no more improvement occurs.

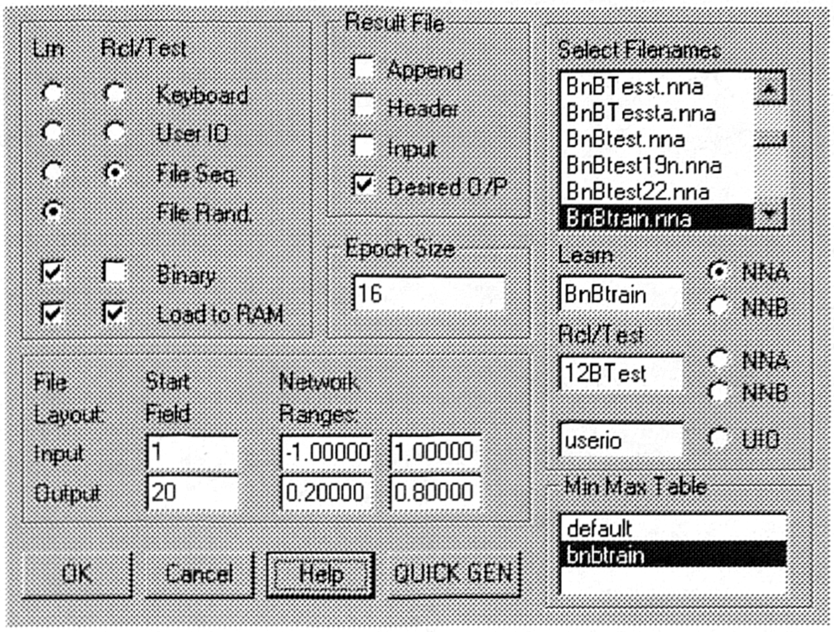



Fig. D.2: I/O parameters

Fig. D.2 shows the I/O parameters used for the initial ANN model (B.Net 1). The following section explains how the MinMax Table is constructed and how the scaling and de-scaling mechanisms are used.

15. Desired O/P:

Shows the desired output and the network results as unscaled data. This is only valid in the "Test" mode. The result file can optionally contain the input and/or desired output for comparison purposes.

**MinMax Table**

A "MinMax Table" is a utility used in conjunction with data I/O file which allows automatic scaling of real world data ranges into ranges within which the network performs better. A network with a hyperbolic tangent transfer function in the output layer produces outputs lying between -1 and +1. For this network, to learn effectively, it is important that the desired outputs lie within this range. Similarly, a network with a sigmoid transfer function performs better if the desired outputs lie between 0 and 1. Mapping the desired real word outputs to the range (0, 1) is achieved using a MinMax Table. The same table is used to scale the real world input values, i.e. raw values, to fall within a certain range (-1, +1) to keep the network from saturation. Also, this table is automatically used to de-scale the network value to real world unites on output.

As explained in previous section, the "File Input Output" (IO) consists of a set of records, i.e. rows, one for each real world example. A record is a set of (n) input fields followed by a set of (m) output fields, where n, m are respectively the number of input and output processing elements in the network. In the case of the initial model (B. Net 1), n = 19 and m = 1. To explain how the MinMax table is constructed and used, let us consider the general case where the network has (n) input nodes and (m) output nodes. In other word, the IO file contains (n+m) data fields, which are denoted as $F_k$. These data fields contain the following real world values:

$F_{i\,1}$, $F_{i\,2}$, ...., $F_{i\,k}$, ....., $F_{i\,n}$, $F_{i\,n+1}$, $F_{i\,n+2}$, ......., $F_{i\,n+m}$

For this IO file, a MinMax Table consists of two sets of values:

$\mathrm{Min}_1$, $\min_2$, ...., $\min_k$, ....., $\min_n$, $\min_{n+1}$, $\min_{n+2}$, ......., $\min_{n+m}$

and

$\max_1$, $\max_2$, ...., $\max_k$, ....., $\max_n$, $\max_{n+1}$, $\max_{n+2}$, ......., $\max_{n+m}$

Where ($i$) is the index of the corresponding data record and ($k$) is the index of the corresponding data field. For a given data field ($F_k$), $\min_k$ and $\max_k$ are typically the minimum and maximum values respectively that the field could have. NeuralWorks software automatically scans the IO file and selects minimum and maximum values for the MinMax Table. However, $\min_k$ and $\max_k$ can be selected by the user whereas $\min_k$ should be less than $\max_k$. The MinMax Table ranges are used in conjunction with the target network ranges selected for the scaled input and output values. This selection is automatically set by the NeuralWorks in correspondence with the input mode (e.g. Bipolar Input mode), the learning rule, and the transfer function used. However, the target network ranges can be reset by the user in the "I/O Parameters" dialogue box (see Fig. D.2). Let the network target ranges for the desired inputs and outputs be denoted respectively by:

($\min_{DI}$, $\max_{DI}$) and ($\min_{DO}$, $\max_{DO}$)

The MinMax Table defines a linear mapping which maps the minimum value of the real world range ($\min_k$) to the minimum value of the desired network range

($min_{DI}$ /$min_{DO}$) and the maximum value of the real world range ($max_k$) to the maximum value of the desired network range ($max_{DI}$/$max_{DO}$). A real world input value ($F_{i\ k}$) in the $(i)_{th}$ record and the $(k)_{th}$ data field of the IO file is mapped to the corresponding desired input value ($f_{i\ k}$) as follows:

$$f_{i\ \ k} = Y(F_{i\ \ k})$$

$$f_{i\ \ k} = \frac{(\max_{DI} - \min_{DI}) * f_{i\ \ k} + (\max_k * \min_{DI} - \min_k * \max_{DI})}{(\max_k - \min_k)} \quad \text{(D.1)}$$

Equation D.1 is visualised in Fig D.3. Similarly, a real world output value ($F_{i\ n+h}$) in the record $(i)_{th}$ and the $(n+h)_{th}$ data field of the IO file is mapped to the corresponding desired output value ($f_{i\ n+h}$) as follows:

$$f_{i\ \ n+h} = G(F_{i\ \ n+h})$$

$$f_{i\ \ n+h} = \frac{(\max_{DO} - \min_{DO}) * F_{i\ \ n+h} + (\max_{n+h} * \min_{DO} - \min_{n+h} * \max_{DO})}{(\max_{n+h} - \min_{n+h})} \quad \text{(D.2)}$$

A raw network output for the $(i)_{th}$ record and the $(n+h)_{th}$ data field ($o_{i\ n+h}$) needs to be de-scaled back to real world value ($O_{i\ n+h}$). The following formula is used to achieve this de-scaling process:

$$O_{i\ \ n+h} = U\ (o_{i\ \ n+h})$$

$$O_{i\ \ n+h} = \frac{(\max_{n+h} - \min_{n+h}) * o_{i\ \ n+h} + (\max_{DO} * \min_{n+h} - \min_{DO} * \max_{n+h})}{(\max_{DO} - \min_{DO})} \quad \text{(D.3)}$$

Values that are outside the MinMax Table ranges ($min_k$ - $max_k$, $min_{n+h}$ - $max_{n+h}$) are mapped linearly outside the target network ranges, ($min_{DI}$ - $max_{DI}$, $min_{DO}$ - $max_{DO}$) using the same scale and offset parameters. Regardless of how the MinMax Table is generated, the same table and the same network ranges should be sued in training, testing and recall phases. The process of scaling a training IO data file into a desired ranges of input and output values and de-scaling the network outputs back to real world values is summarised in Fig. D.4.

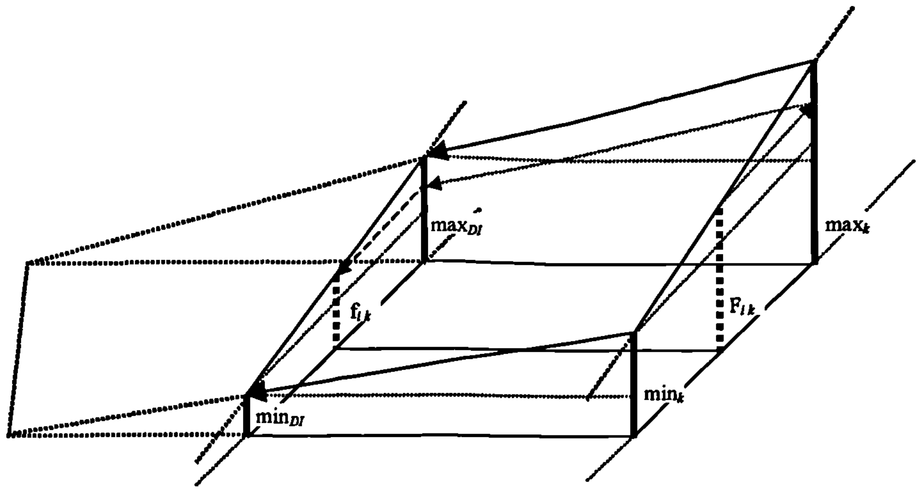



Fig. D.3: Scaling the actual input/ output values to the desired values

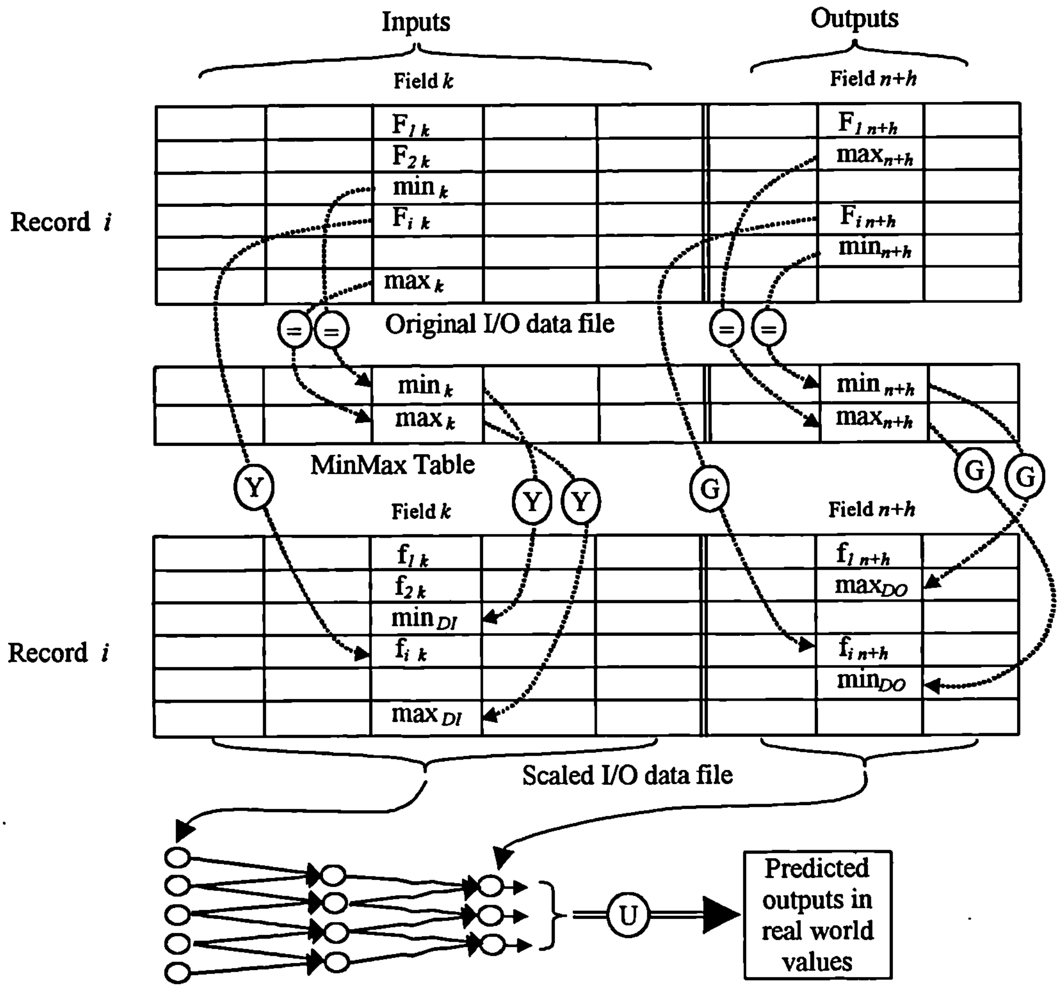



Fig. D.4: Scaling/de-scaling of training/ testing data

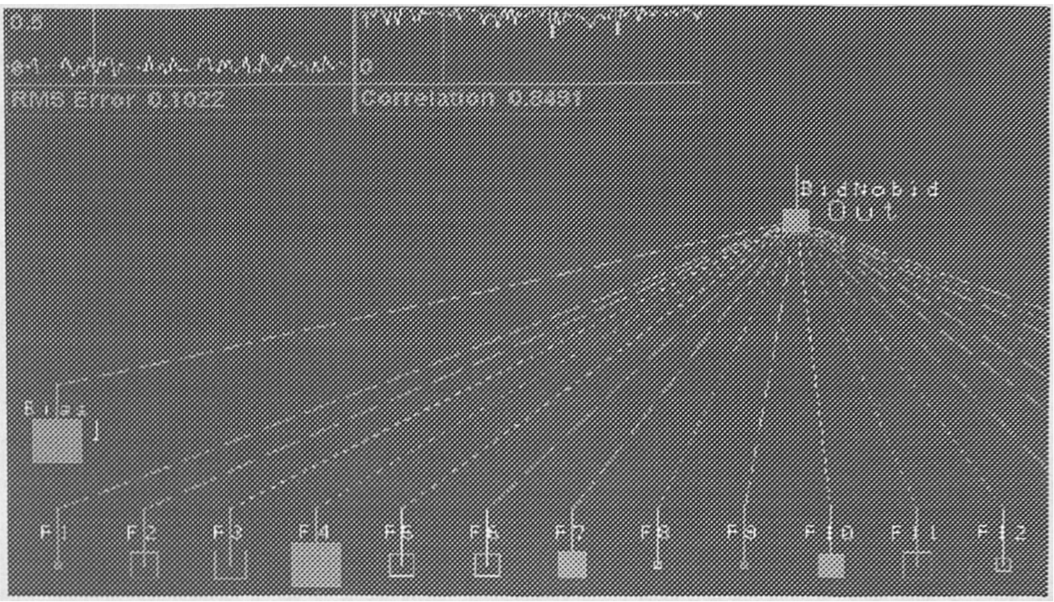



Fig. D.5: Training performance of model B. net1 after 50000 iterations

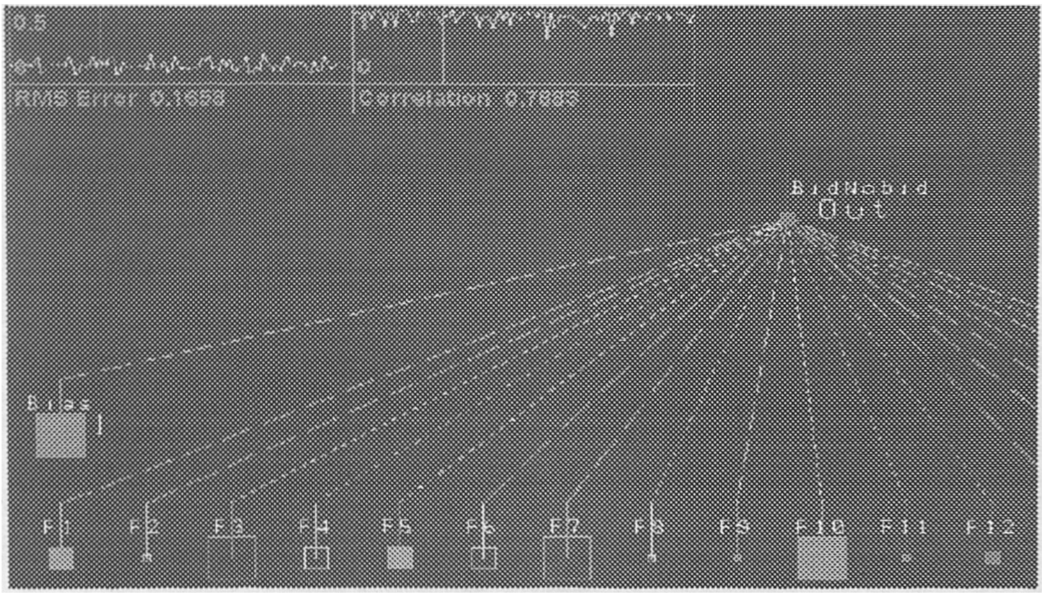



Fig. D.6: Generalisation performance of the trained B. net1 model

**Format of the Input and Output (IO)files of training and testing ANN model**

1. The NeuralWorks supports a general "File Input and output (IO)" format for reading data in to a network. This format encompasses standard field delimited data file formats in which data fields, i.e. variables, are separated by commas, spaces of tabs and records, i.e. cases, are separated by lines. A data file (IO) is a set of rows of data fields where each row corresponds to a complete record and each column corresponds to particular processing element in the input or output layers

   Features of IO include the following (NeuralWorks reference guide):

   - A simple standard file format compatible with spreadsheet and database interfaces;
   - Binary option leading to faster IO;
   - Run-time randomisation of the order of presentation of input data;
   - Automatic scaling and offsetting of data values at both input and output;
   - The ability to easily compare test results with desired output to measure network performance; and,
   - User override of automatic features.

**Training by Back Propagation**

The flow of the training B. net1 operations can be explained as follows:

1. Each input node receives input signals form a record with an index ($r$) in the scaled I/O data file, which contains 162 records and 20 fields, and forwards this signal to the output processing element. Let this record be denoted by 1 ($r$=1). The selection of which cases to be presented to the network is random as this option was selected in the initial design phase;
2. The output processing element sums the weighted signals received form the input buffer:

$$X_r = \sum_{0}^{19} (f_i * W_i) \qquad \text{(D.4)}$$

   And, then, applies its activation function (sigmoid transfer function) to compute its output signal for the record r ($O_r$):

$$O_r = (1 + e^{-X_r})^{-1} \qquad \text{(D.5)}$$

3. This output signal (O) is compared to the desired output (dO) corresponding to the same record to compute that global error (E):

$$E_r = 0.5 * (dO_r - O_r)^2 \tag{D.6}$$

The global error is stored in the current error field. The error that needs to be propagated back to the previous layer is the "scaled local error" (e):

$$e_r = (dO_r - O_r) * O_r * (1 - O_r) \tag{D.7}$$

This error is stored in the error field of the processing element. This completes the first learning cycle;

4. Another record ($r$=2) is selected and presented to the network. The scaled local error is computed and stored for this record in the same way;
5. As the "cumulative delta rule" learning method is adopted, the connection weights are not updated at the end of each cycle. Instead, step 4 is repeated to complete the number of cycles to 16, i.e. the selected epoch size, and the local errors are accumulated. The average of the scaled local errors of the 16 cases is computed:

$$e = \sum_{1}^{16} e_r \tag{D.8}$$

This error is used to update the current connection weights;

6. Each connection weight ($W_i$) is modified by adding its delta weight ($\Delta W_i$) to its previous value:

$$\Delta W_i = Lcoef * e * f_i + \eta * \Delta W_i' \tag{D.9}$$

Where:

Lcoef. is the leaning coefficient (currently 0.3);

$\eta$ is the momentum parameter (0.4); and,

$\Delta W_i'$ is the previous delta weight for connection $i$ (currently 0);

7. Another 16 cases are selected and presented to the network and the average local error is computed and the connection weights are updated is the same way;

8. Step 7 is repeated so all the data records are presented to the network. By presenting all the records, one learning iteration is completed;
9. The same process is repeated for 50000 iterations. For the first 10000 iterations (the selected transfer point ,i.e. Tarns. Pt., as shown in Fig. D.6), the Lcoef. is (0.3). For iterations from 10000 to 30000 (three times Trans. Pt.), the Lcoef. is reduced to (0.5*0.3=0.15). For iterations from 30000 to 50000, the Lcoef. is reduced again to (0.5*0.15 = 0.075). Where the learning the coefficient ratio (Lcoef. Ratio) is (0.5);
10. When the learning count reaches the pre-selected limit (50 000), the training is ceased automatically. The functional relationship between the nineteen bidding factors and the "bid/ no bid" decision is captured, to some extend, in the memory, i.e. connection weight, of the trained B. net1 model. The final weights are used to predict the actual decisions in the 162 cases included in the scaled I/O training data file. Two statistical measures of how close the predicted decisions to the actual ones are provided by the NeuralWorks software as shown in Fig. D.5. These measures, i.e. diagnostic instruments, are $RMS_{train}$ (root mean square error) and $R^2_{train}$ (correlation coefficient); and,
11. $RMS_{train}$ and $R^2_{train}$ of model (B. net1) are recorded in one table (Table 6.15).

# APPENDIX E

# RELATED PUBLICATIONS


Wanous, M., Boussabaine, A.H. and Lewis, J. (1998). Tendering factors considered by Syrian contractors. ARCOM, 14th Annual Conference Proceedings, Vol. 2, pp. 535-534, Oxford, England.

Wanous, M., Boussabaine, A.H. and Lewis, J. (1999). A qualitative bidding model. ARCOM, 15th Annual Conference Proceedings, Vol. 2, pp 625-634. Liverpool, England.

Wanous, M., Boussabaine, A.H. and Lewis, J. (2000a). to bid or not to bid: a parametric solution. Construction Management and Economics, Vol. 18, No. 4, pp. 457-467.

Wanous, M., Boussabaine, A.H. and Lewis, J. (2000b). A neural networks decision-support system for bidding in construction. 17th International Symposium on automation and Robotics in Construction (ISARC 2000). Taipei, Taiwan, pp783-786.

Wanous, M., Boussabaine, A.H. and Lewis, J. (2001). A fuzzy decision-support system for competitive tendering. First International Structural Engineering and construction Conference. Honolulu, Hawaii, USA. In press.

# TENDERING FACTORS CONSIDERED BY SYRIAN CONTRACTORS

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For construction contractors, it is not an easy decision whether to bid or not to bid for a new project. That involves quantifying the combined impact of many factors and then producing a quick cost estimation for the project. All that should be done within a short limited time. Developing a decision-support system for making "bid/ no bid" and "mark up size" decisions will be of great help to contractors. This paper reports the progress of the first stage of developing a decision-support system to help contractors in bidding situations. The Syrian tendering system is presented and, through a questionnaire survey supported by six semi-structured interviews with interested expert contractors, thirty-eight factors were uncovered and ranked according to their importance to contractors operating in Syria. Meeting the "to-tender" conditions, financial capability of the client, and relations with and reputation of the client are the most important factors in the bidding decision. On the other hand, relation with other contractors/suppliers, the proportions to be subcontracted and the local customs are the least important factors in making this decision.

Keywords: Practical bidding model, bid/no bid criteria, Syria.

## INTRODUCTION

It is generally accepted that all construction projects are liable, to some extent, to be affected by uncertainty. The contractor's journey through uncertainties and risks associated with a new construction project starts when an invitation to bid for this project is received. Contractors should decide whether to bid or not. Consequently, if the decision was to bid, the mark up size will need to be determined. The "bid/ no bid" and "mark up size" decisions are complex. This complexity is due to their monetary importance and because they are influenced by many interrelated factors.

Most of the current bidding models emphasise the "mark up size" decision more than "bid/ no bid" decision. These models tend to produce a recommendation for the mark up size decision and then try to assist in making the bidding decision. That is not the case in the construction practice where a contractor starts with making "bid/ no bid" decision and only if the decision was to bid the contractor will study the project in depth to determine a proper mark up percentage.

The main purpose of this study is to identify the parameters that characterise the bidding decision in Syria and to develop a bidding model that reflects how contractors make this decision in practice. This model is based on the findings of six semi-structured interviews conducted among interested expert contractors and , through a written questionnaire survey, thirty eight factors were identified and ranked according to their importance in making the "bid/ no bid" decision.

That is the first step of a study being carried out to develop a decision-support system that will be able to help contractors in making "bid/ no bid" decision and, if required, the "mark up size" decision.

## PREVIOUS STUDIES

The literature contains a great deal of theoretical bidding models based on the works of Friedman (1956) and Gates (1967). All these mathematical models proved to be suitable for academia but not for practitioners. Gates (1983) introduced a none-mathematical bidding strategy based on ESPE (Expert Subjective Pragmatic Estimate). Ahmad and Minkarah (1988) concluded that only 11.1% of top American contractors use some sort of mathematical models. Very few qualitative studies, which study how the bidding decisions are made in practice, have been carried out. Ahmad and Minkarah (1987) developed an optimum mark up bidding approach and, in 1988, they conducted a questionnaire survey to uncover the factors that characterise the bidding decision-making process in the United States. This survey revealed that type of job; need of work and the client are major bidding criteria in the United States.

Moselhi *et al.* (1991) demonstrated, by the way of an example, how neural networks could be used to develop a mark up model. They concluded that neural networks could be integrated with expert systems to form an ideal decision support system. Shash and Abdul-Hadi (1992) presented thirty seven factors affecting the mark up size decision with their relevant importance to contractors operating in Saudi Arabia. They concluded that contract size, availability of the required cash and type of contract are the most important factors to contractors in Saudi Arabia.

Shash (1993) concluded that need of work, number of competitors tendering and experience in similar projects are the most important amongst fifty five factors that affect the bid/ no bid decision in the UK.

Moselhi *et al.* (1993) implemented a neural network application to develop an analogy-based decision support system for bidding in construction. This model accounted for the uncertainties in the contractor's assessment of the project's risks by a sensitivity analysis conducted using Monte Carlo simulation technique. Hegazy (1993) developed a prototype for integrated bid preparation with emphasis on risk assessment using neural networks. This prototype was designed to produce an optimum mark up value that maximise the potential profit and predicts the probability of winning the contract at such profit and then data obtained through detailed cost estimate will be utilized to optimally unbalance the final bid.

Schroeder (1993) combined bidding models using the theories of utility, probability, and present value concepts to develop an integrated construction bidding system for the purpose of determining a bid mark up on a construction tender.

Abdelrazig, A. A. (1995) considered thirty-seven factors that affect the bid/ no bid decision in Saudi Arabia and utilized an analytic hierarchy process to develop computer software called Expert Choice to help contractors in this decision. Dozzi *et al.* (1996) developed a utility theory model using twenty one criteria for bid mark up determination. This model is, generally, complex and it assumes that the higher the competition the higher the mark up which is not the generally accepted view of how the competition works.

# TENDERING SYSTEM IN SYRIA

Every registered contractor regularly receives a copy of the Bulletin of Official Tenders (BOTs), which is an open invitation to bid for a very wide range of projects that the construction industry's clients (usually the public sector agencies) intend to construct. The BOTs usually contain the following information about each of the advertised projects:

(1) The project location; (2) The project name (type); (3) The project size; (4) The estimated project duration; (5) The client identity; (6) Conditions that should be met by the tendering contractors; (7) The place where to submit the bids; (8) Bids' submission date; (9) Date of bid opening; (10) The temporary deposit (bid bond); (11) The final deposit (performance bond); (12) The place where the complete specifications and drawings are available; (13) The code of technical, financial, and legal conditions that would be applied; (14) The duration within which the contractor will be committed to his offer; (15) Number of announcements made to the same project so far; (16) Type of the tendering procedure.

The two most frequently used tendering procedures adopted in the Syrian construction industry are:

1. Addition / Reduction Tender (A/RT): In this case the client's design department produces the project's cost estimate, bill of quantities (all items are included with their standard units, quantities, individual prices and cumulative prices), detailed specifications, drawings and the codes of technical, financial, and legal conditions. Then the project is advertised in the Bulletin of Official Tenders and, sometimes, in the local/ national newspapers. Interested contractors can compete on this project by submitting a bid in a sealed envelop, which is an offer to construct the project within the client-estimated cost increased or reduced by a certain percentage, which would be compared with other competitors' percentages.
2. Price Offer Tender (POT): Very similar to the A/RT but the client is not involved in a detailed cost estimate. The bills of quantities contain only the items' descriptions, standard units, and approximate quantities. Interested contractors fill in the missing individual prices and cumulative prices for each item and then, by summing up the cumulative prices, calculate the final price, which would be compared to other competitors' prices.

The lowest bid will win the contract. There are some other procedures such as direct negotiation, which is used by some agencies for small projects.

# DATA COLLECTION

The general nature of this approach dictated what data is required and how to collect it. Two techniques were adopted in the process of gathering the required data. Six semi-structured interviews were conducted among interested expert contractors to gain an overall understanding of how Syrian contractors make "bid/ no bid" and "mark up" decisions in practice. A formal questionnaire survey was designed and mailed to randomly selected contractors

### Semi-Structured Interviews

This technique has some of the advantages of reliability, structure, and control associated with more structured interviews and some of the advantages of the scope, flexibility of responses obtainable by less structured interviews. Six semi-structured interviews were conducted among interested and successful contractors with considerable experience (19-31 years) in the Syrian construction industry. The main objective of these interviews was to gain an overall understanding of how contractors make their tendering decisions in practice. Certain open-ended questions (e.g. please explain how you make the bid/ no bid decision, when it is recommended not to bid for a new project,) were asked in the same order. The interviews were tape-recorded and a written report was produced for each one.

Interviewees agreed that contractors start studying a new project by skimming through the BOTs with attention paid to the following points:

(1) Relations with/ reputation of the client;
(2) Financial capability of the client;
(3) Project Size;
(4) Fulfilling the to-tender conditions imposed by the client;
(5) Availability of capital required;
(6) and the availability of time for tendering.
After considering these factors, if "no bid" decision has not been made, contractors will proceed and buy a copy of the related conditions, specifications and drawings from the client's contract division. Sometimes, contractors prefer to visit the intended project site. However, this has not been considered necessary in some situations (e.g. small building projects). Then contractors will study, in some details, the related drawing, specifications, and the other financial and legal conditions. In this stage the following points will be emphasised:

(1) Risks expected due to the project's nature; (2) Method of construction (manually or mechanically); (3) Rigidity of specifications and conditions.

Contractors also consider other factors (e.g. experience in similar projects, availability of qualified staff, availability of equipment, availability of materials required, availability of other projects).

Usually contractors combine the effects of all the mentioned factors and then decide whether to bid or not. No single factor is enough to make bid decision but sometimes a single factor could be enough to make "no bid" decision. Each of the following factors was considered to be enough, in itself, for making "no bid" decision:

1- The project size is lower than the contractor's interest.
2- The project size is higher than the contractor's capacity.
3- The contractor has very low experience in such a project.
4- Bad reputation of the client.
5- Low financial capability of the client.
6- Many problems with the public about the project's site.
7- The required cash can not be available.
8- The to-tender conditions imposed by the client cannot be fully met.
The bidding strategy explained here before was translated into a bidding model that reflects how the "bid/ no bid" decision is made in practice. This model is outlined in Figure 1.

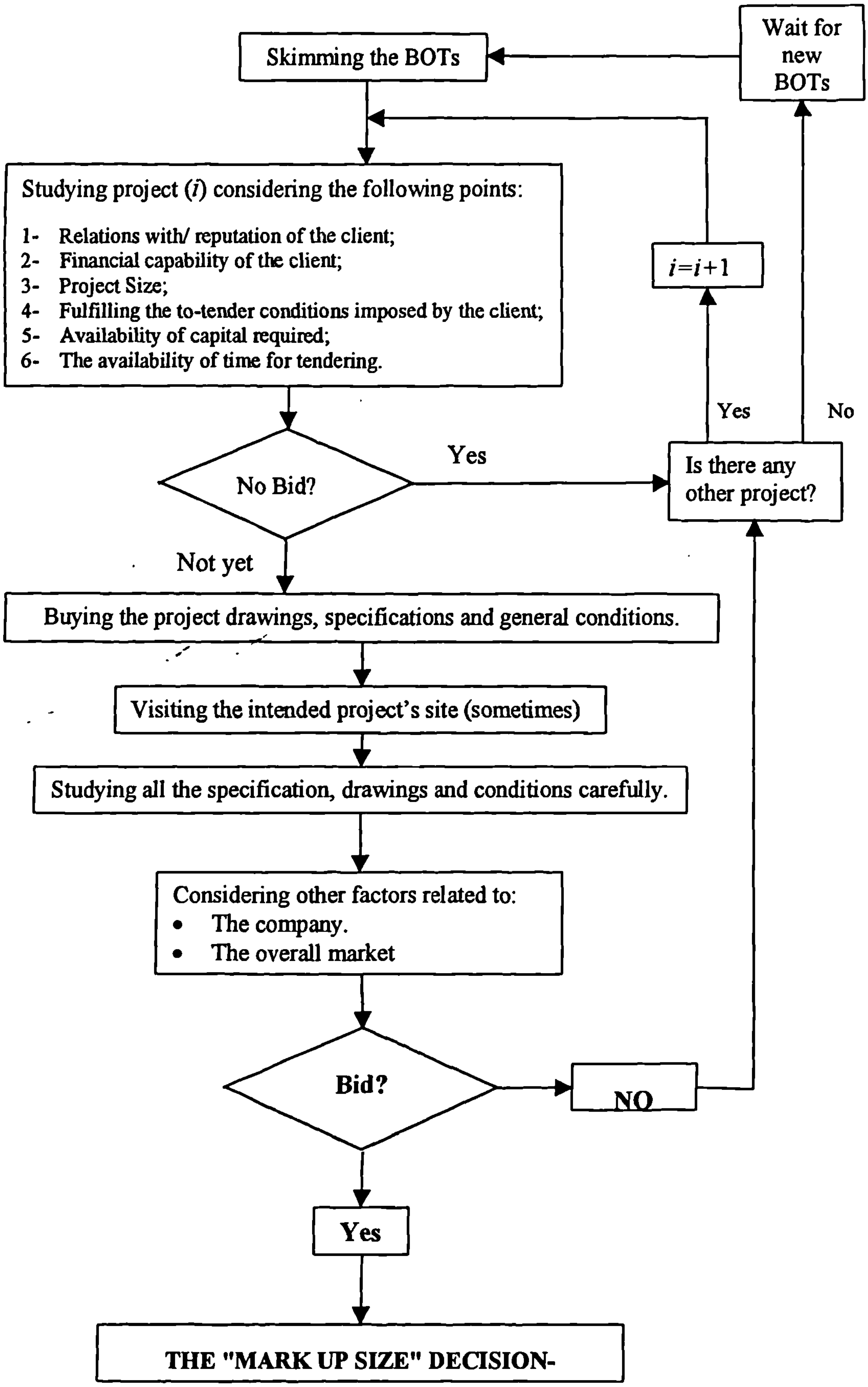


**Figure 1**: The "bid/no bid" decision

**Sample Selection**
The sample was selected from the 1996 classified private contractors/ companies list provided by the Syrian Contractors Association.

The following formula was implemented to determine the required sample size (Parasuraman 1990):

$$n_{\max} = \frac{z_q^{\;2} \times s^2}{H^2} \qquad (1)$$

Where $n_{max}$: the sample size; s: the estimated standard deviation in the population elements; $z_q$ : the normal standard-deviate value corresponding to a q% confidence level in the interval estimate; H: the desired level of precision.

For normal distribution, the standard deviation (s) can be estimated as follows:

S=(maximum value-minimum value)/6 (2)

For this study, the contractors' years of experience was considered as the population's parameter.

The lest, i.e. sampling frame, provided by the Syrian Contractors Association contained 2231 contractors (the total population) with (1 to 35) years of experience in the Syrian construction industry.

The normal distribution was assumed. Thus the standard deviation could be estimated using formula (2): s = (35-1)/ 6 = 5.667

Also, for a normal distribution, we can estimate the mean value (years of experience) as: M= (35-1)/2=16 years

The mean value "years of experience" of the required sample was considered to be acceptable in the range M±2 years, i.e. H=2.

To achieved that in 99% confidence level ($z_q$ = 2.575), the formula (1) can be used to calculate the required sample size as follows:

$n_{max} = (2.575)^2 * (5.667)^2 / 2^2 = 53.25$

A sample of fifty responses was assumed to be enough to give an indication of the importance level for each of the bidding parameters. Response rate of 25% was expected, thus 200 companies/ contractors were randomly selected and approached by the way of formal questionnaire along with an accompanying letter explaining the purpose of the survey. Sixty-one Syrian contractors filled in and returned the questionnaire. The response rate was higher than expected (30.5%).

**Factors Affecting The "Bid/ No Bid" Decision**
Using the scores given by the contractors, an importance index ($I_j$) was produced for each factor ($F_j$).

Ahmad and Minkara (1988) considered the percentage of the respondents who scored a factor by 4 or higher (in a range of 1to 6) as an importance index for this factor. Shash (1993) implemented the following formula:

Importance index = Σ (a * X) * 100/7 (3)

Where a: is a weight, (1 ≤ a ≤7), given to the factor in each response.

$X = n/N$; n: frequency of response; N: Total number of responses.

$\Sigma (a * X) = \Sigma (a * n/N)$, which is the weighted average of a.

In this paper the weighted average was produced using the following formula:

$$M_j = \frac{\sum_{i=0}^{i=6} (s_{ij} * n_{ij})}{N_j} \qquad (4)$$

Where $M_j$: the mean importance level of factor $j$;
$s_{ij}$: score between 0 and 6 given to factor $j$ by each contractor;
$n_{ij}$: number of contractors who scored factor $j$ by $s_{ij}$;

$N_j$: number of contractors who gave a score to factor $j$. $N_j \leq N = 61$ (total number of respondents). That to discount the missing values' effects.

The score of 6 represents 100% importance. Thus the importance index $I_j$ for factor $j$ was computed using the following formula:

$$I_j = M_j * \frac{100}{6} \qquad (5)$$

Table 3 represents thirty-eight factors in a descending order of importance in making the "Bid/ no bid" decision in Syria.

In the case of two, or more, factors having the same importance index, the factor whose Skewness is greater was ranked first because that indicates that more extreme scores are greater than the mean.

Fulfilling the to-tender conditions, i. e. qualifications, imposed by the client was ranked the first among 38 factors that affect the bidding decision. It was given a very high importance (89.88%) but not 100% presumably because a contractor who does not fully meet the required conditions can submit a tender in partnership with other contractors who do fulfil these conditions.

Avai ıbility of the required capital was ranked the sixth with a high importance (68.33%), which is less than expected perhaps because contractors can borrow the capital they require until they receive the first payment from the client. That will affect, to some extend, their mark up. On the other hand a moderate importance was assigned to the expected risks, which have more effect on the "mark up size" decision. Surprisingly the project location was assessed as a very low important factor in the bidding decision. Very little importance was assigned to competition. Number of competitors and competence of the expected competitors were ranked thirty second and thirty sixth respectively. Fluctuation in labour/materials' prices has little effect on "bid/ no bid" decision because labour/ materials' prices are currently very stable in Syria.

The mark up decision is out of the paper scope. However it is worth noting that the same aforementioned factors affect the mark up size decision but to different degrees.

For example risks expected, which is the eighteenth bidding criterion was ranked the first amongst thirty eight factors that affect the mark up decision.

**Table 1**: "Bid/ no bid" factors in descending order of importance

| **Factors** | | **Mean (MJ)** | **Importance** |
|---|---|---|---|
| j | | 0----6 | Index Ij |
| 1 | Fulfilling the to-tender conditions imposed by the client. | 5.39 | 89.88% |
| 2 | Financial capability of the client. | 4.66 | 77.67% |
| 3 | Relations with and reputation of the client. | 4.61 | 76.83% |
| 4 | Project size. | 4.39 | 73.17% |
| 5 | Availability of time for tendering. | 4.25 | 70.83% |
| 6 | Availability of capital required. | 4.10 | 68.33% |
| 7 | Site clearance of obstructions. | 4.08 | 68.00% |
| 8 | Public objection. | 4.07 | 67.83% |
| 9 | Availability of materials required. | 3.98 | 66.33% |
| 10 | Current work load. | 3.95 | 65.83% |
| 11 | Availability of equipment required | 3.84 | 64.00% |
| 12 | Experience in similar projects | 3.84 | 64.00% |
| 13 | Method of construction (manually, mechanically). | 3.84 | 64.00% |
| 14 | Availability of skilled labour. | 3.48 | 58.00% |
| 15 | Availability of qualified staff. | 3.34 | 55.67% |
| 16 | Original project duration. | 3.33 | 55.50% |
| 17 | Site accessibility. | 3.23 | 53.83% |
| 18 | Risks expected. | 3.13 | 52.17% |
| 19 | Degree of hazard. | 3.13 | 52.17% |
| 20 | Rigidity of specifications. | 3.00 | 50.00% |
| 21 | Expected project cash flow. | 2.82 | 47.00% |
| 22 | Degree of builability. | 2.82 | 47.00% |
| 23 | Availability of other projects. | 2.77 | 46.17% |
| 24 | Confidence in the cost estimate. | 2.72 | 45.33% |
| 25 | The project geological study. | 2.41 | 40.17% |
| 26 | Project location. | 1.90 | 31.67% |
| 27 | Original price estimated by the client. | 1.71 | 28.50% |
| 28 | Past profit in similar projects. | 1.59 | 26.50% |
| 29 | Expected date of commencing. | 1.48 | 24.67% |
| 30 | Availability of equipment owned by the contractor. | 1.33 | 22.17% |
| 31 | Expected number of competitors (Degree of competition). | 1.07 | 17.83% |
| 32 | Local climate. | 1.05 | 17.50% |
| 33 | Specific features that provide competitive advantage. | 0.98 | 16.33% |
| 34 | Fluctuation in labour/ materials price. | 0.90 | 15.00% |
| 35 | Competence of the expected competitors. | 0.75 | 12.50% |
| 36 | Relations with other contractors and suppliers. | 0.62 | 10.33% |
| 37 | Proportions to be subcontracted. | 0.33 | 5.50% |
| 38 | Local customs. | 0.25 | 4.17% |

## CONCLUSION

This paper reports the findings of six semi-structured interviews and a questionnaire survey conducted among randomly selected contractors operating in Syria. The interviews' findings were translated into a bidding model that reflects how "bid/ no bid" decision is made in practice. Thirty eight factors were ranked according to the influence they have on "bid/no bid" decision as Syrian contractors have assessed them. Meeting the to-tender conditions, financial capability of the client and relation with/ reputation of the client are the most important factors in making "bid/ no bid" decision in Syria. The findings of past similar studies were referred to. Need of work, number of competitors tendering and experience in similar projects are the major bidding factors in the UK. Type of job, need of work and the owner are major bidding criteria in the United States.

The finding of this survey will be used to develop a decision-support to help contractors in making "bid/ no bid" decision and then, if required, determining a competitive mark up percentage. In the case of many new projects, the system could recommend the most suitable project for bidding.

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# A QUALITATIVE BIDDING MODEL

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Competitive bidding is one of the most critical activities for contractors in the construction industry. Contractors must first decide whether to bid or not and, if the bid decision was made, a suitable mark up percentage needs to be selected. The usual practice is to make these decisions on the basis of intuition derived from a mixture of gut feelings, experience and guesses. Numerous factors are involved in this process making it very difficult even for experienced contractors to always make the right decision within the available time. Thus it is necessary to have some type of structured solution for the bidding problem.

Many models have been developed for the second part of the bidding problem, i.e. the mark up selection. However, very few publications can be found about the bid/no-bid decision, which should be made first before selecting a proper mark up. The development process of a qualitative bidding model is reported. First, the most important bidding criteria in Syria were identified and a parametric model was developed for each one. A new bidding situation was evaluated in terms of these criteria and a bidding index was produced for it. Based on this index, the model will recommend to bid or not to bid on the project under consideration. The proposed model was tested against one hundred and eighty two real bidding situations and proved 92.86% accurate in simulating the contractors' decisions.

Keywords; bid/no-bid criteria, qualitative bidding, Syria, tendering.

## INTRODUCTION

Contractors' survival is strongly dependent on being able to deal successfully with different bidding situations. Bidding for an unsuitable project could result in a disaster, large losses or consuming time and resources that could be invested in more profitable projects. Not bidding for a suitable project could result in losing an opportunity to make considerable profit, improve the contractors' strength in the industry, gain a new relation with a new client etc.

Also, if a contractor decided to bid for a new project, he needs to make another difficult decision that is to determine a suitable mark up percentage for this project. Bidding for a new project commits the bidder to bid preparation costs. Thus, contractors have to be more selective in bidding to reduce these costs. The need for automated system to assist contractors in dealing with different bidding situations has resulted in research over a long period. The first half of the bidding process, i.e. the bid/ no bid decision, has received very little attention from researchers. On the other hand, many bidding models have been developed for the second half of the bidding problem, i.e. selecting the optimum mark up. These models are based on mathematical theory and attempt to simulate the real world situation. Most of the mathematical models are based on Freidman's model (1956).

The main aim of these models is to compute the probability of winning the contract for a certain mark up. Although determining the probability of wining is an important part of the bidding decision-making process, it is not all. It should be complemented with considering the impact of many other factors. These models have not been popular amongst practitioners for various reasons, including the large amount of data-tracking and calculations required for implementing them. The usual practice is to make the decision on the basis of intuition derived from a mixture of gut feelings, experience and guesses. Numerous factors are involved in this process. Thus it necessary to have some type of structured approach to deal with it.

The main objective of this paper is to develop a qualitative bidding model to help contractors in systematically evaluating the bidding situation of a new project and recommend a bid/no-bid decision. If many new projects are available for bidding, the model can help in selecting the most suitable one. Also the model in useful to carry out a what-if analysis for a single project.

The development process of a qualitative bidding model is explained below. First, the most important factors that characterize the bidding process in Syria were identified and a parametric model was developed for each one. A bidding index was produced. Based on this index, the model will recommend either to bid or not to bid for the project. The proposed model was tested on 182 real bidding situations. It proved 93% accurate in simulating experienced contractors' decisions.

## LITERATURE REVIEW

The literature contains a great number of theoretical bidding models based on the works of Friedman (1956) and Gates (1967). All these mathematical models proved to be suitable for academia but not for practitioners. Very few qualitative approaches, which study how the bidding decisions are made in practice, have been carried out.

Ahmad and Minkarah (1988) conducted a questionnaire survey to uncover the factors that characterized the bidding decision-making process in the United States. Subsequently, Ahmad (1990) proposed a bidding methodology based on the decision analysis technique for dealing with the bidding problem. In this model, the bidding problem is decomposed into four high-level criteria and thirteen lower-level criteria. This model demands many inputs some of which the bidder, especially those with limited experience, might not be able to provide. Also, it assumes that all factors contribute positively to the total worth, i.e. desirability, of the project under consideration. No distinction was made between some factors that count for the total worth, such as profitability, and others that count against the total worth, such as "degree of hazard". However, this approach is the most promising step on the road to modelling the bid/no-bid decision.

Ahuja and Arunachalam (1984) proposed a model to aid contractors in systematically evaluating the risk due to the uncertainty of availability of required resources before bidding on a new project. A CPM summary network, with resources allocation, was required for this model. In fact, this model could be viewed as a resource allocation model but not as a bid/no-bid model. It does not have clear criteria to give a bid or no bid recommendation. Resources, and risks related to them, are not the only criteria that affect the bid/no-bid decision-making process.

Abdelrazig (1995) carried out a literature review and identified 37 factors that affect the bid/no-bid decision. The analytic hierarchy process (AHP) was utilized and computer software named Expert Choice was developed to help contractors in Saudi Arabia in making their bid/no-bid decisions.

Wanous *et al.* (1998) conducted a questionnaire survey among Syrian contractors to uncover the parameters that characterize their bid/no-bid decision-making process. Thirty-eight parameters were ranked according to their relative importance in making the decision in Syria. It was concluded that fulfilling the "to-tender" conditions, financial capability of the client, and relation with/ reputation of the client are the most important factors.

## THE MODELLING PROCESS

The bid/no-bid decision is a binary decision-making process, having only two possible outputs. However, the influences of various internal and external factors make it a very complex process.

A good point to start developing a structured model for this process is identifying the factors that affect it. Thirty-eight factors that influence the bid/ no bid decision in Syria were uncovered by Wanous (1998). Table 1 represents these factors in a descending order according to their importance indices (Ib).

It seemed, from a simple correlation analysis, that contractors did not differentiate between the "risk expected" factor and the "degree of hazard" factor and between the "availability of skilled labour" and "the availability of qualified staff". Also, the "project's geological study" factor is assumed to be included in the "risk expected" factor. Thus, three factors, degree of hazard, availability of qualified staff and the project's geological study, were omitted to eliminate double counting for the same factor.

The importance indices for the remaining 35 factors are illustrated in Figure 1. For simplicity, it was decided to discount the factors whose importance indices are less than the cut-off point (A). The remaining 22 factors were grouped into two sets. The factors that count for the "bid" decision, i.e. encouraging factors, and the factors that count against the "bid" decision, i.e. discouraging factors. To structure the decision process, a parametric model was developed for each factor (Figures 2a and 2b), where:

$Ib_i$: is the importance index for an encouraging factor $F_i$;

$NB_i$: is the minimum acceptable level of $F_i$, i.e. below this parameter the factor $F_i$ will be enough to cause a "no bid" decision;

$B_i$: is a neutral score below which the factor $F_i$ will have a negative contribution to the "bid" decision and above it this factor will have a positive contribution;

$Ib_j$: is the importance index for a discouraging factor $F_j$;

$NB_j$: is the maximum acceptable level of $F_j$, i.e. above this parameter the factor $F_j$ will be enough to cause a "no bid" decision; and,

$B_j$: is a neutral score above which the factor $F_j$ will have a negative contribution to the "bid" decision and below it this factor will have a positive contribution.

**Table 1:** Bid/no-bid criteria

| **Bid/no-bid criteria** | **Importance index (Ib) (%)** |
|---|---|
| 1. Fulfilling the to-tender conditions imposed by the client | 90 |
| 2. Financial capability of the client | 78 |
| 3. Relations with and reputation of the client | 77 |
| 4. Project size | 73 |
| 5. Availability of time for tendering | 71 |
| 6. Availability of capital required | 68 |
| 7. Site clearance of obstructions | 68 |
| 8. Public objection | 68 |
| 9. Availability of materials required | 66 |
| 10. Current work load | 66 |
| 11. Experience in similar projects | 64 |
| 12. Availability of equipment required | 64 |
| 13. Method of construction (manually, mechanically) | 64 |
| 14. Availability of skilled labour | 58 |
| 15. Availability of qualified staff | 56 |
| 16. Original project duration | 56 |
| 17. Site accessibility | 54 |
| 18. Risks expected | 52 |
| 19. Degree of hazard | 52 |
| 20. Rigidity of specifications | 50 |
| 21. Expected project cash flow | 47 |
| 22. Degree of buildability | 47 |
| 23. Availability of other projects | 46 |
| 24. Confidence in the cost estimate | 45 |
| 25. The project's geological study | 40 |
| 26. Project location | 32 |
| 27. Original price estimated by the client | 29 |
| 28. Past profit in similar projects | 27 |
| 29. Expected date of commencing | 25 |
| 30. Availability of equipment owned by the contractor | 22 |
| 31. Expected number of competitors (Degree of competition) | 18 |
| 32. Local climate | 18 |
| 33. Specific features that provide competitive advantage | 16 |
| 34. Fluctuation in labour/ materials price | 15 |
| 35. Competence of the expected competitors | 13 |
| 36. Relations with other contractors and suppliers | 10 |
| 37. Proportions to be sub-contracted | 6 |
| 38. Local customs | 4 |

$Ib_j$ / $Ib_j$ ; $B_i$ / $B_j$; $NB_i$ / $NB_j$ were identified through a questionnaire survey and semi-structured interviews conducted among Syrian contractors. A contribution index for each bidding factor is produced and, then, a bidding index (BI) is computed for the new bidding situation under consideration.

The contribution of an encouraging factor $F_i$ is computed by the following formula:

$$C_i = Ib_i * (CA_i - B_i) \qquad (1)$$

Where:

$CA_i$: is the contractor's assessment of the Factor $F_i$ to reflect the bidding situation under consideration.

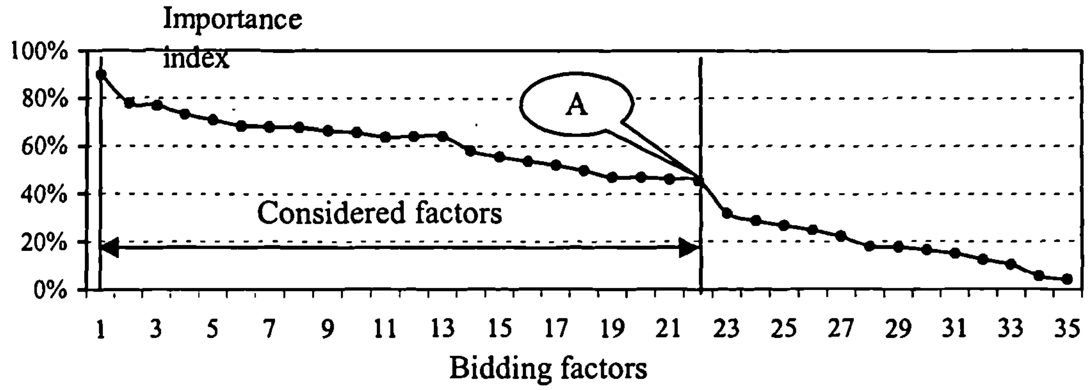


**Figure 1:** selecting the most important bidding factors

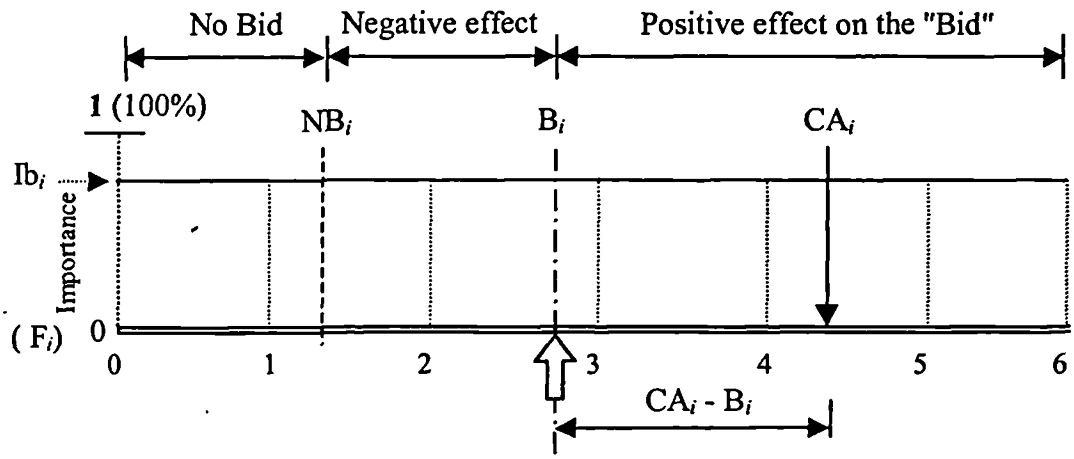


**Figure 2a:** A parametric model for an encouraging factor

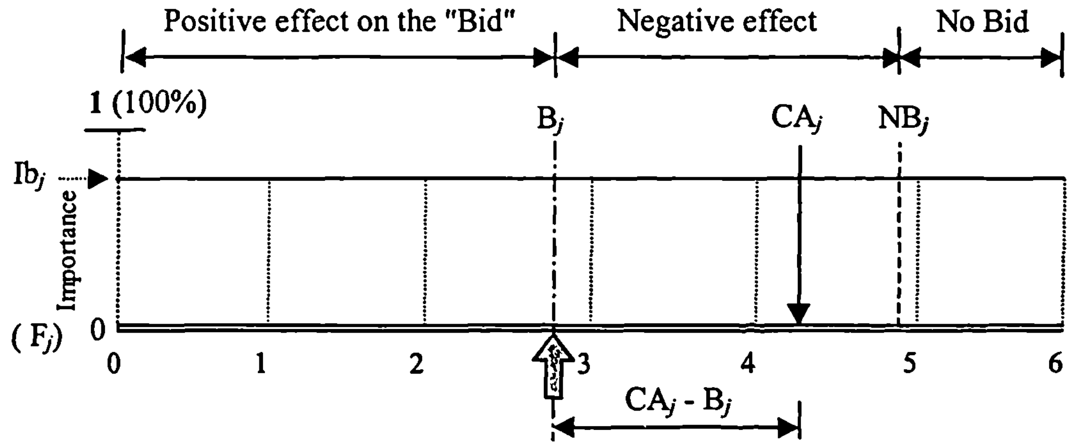


**Figure 2b:** A parametric model for a discouraging factor

**Table 2a:** Encouraging bidding factors in descending order of importance

| *i* | Encouraging Factors | Standard Deviation | Bi Score | Importance Index Ib*i* | Nb*i* |
|---|---|---|---|---|---|
| 1. | Fulfilling the to-tender conditions | 0.37 | 5.84 | 0.90 | 5 |
| 2. | Financial capability of the client | 0.88 | 3.48 | 0.78 | 2 |
| 3. | Relation with/ reputation of the client | 0.78 | 3.84 | 0.77 | 2 |
| 4. | Availability of time for tendering | 1.09 | 2.54 | 0.71 | 0 |
| 5. | Availability of capital required | 0.73 | 3.41 | 0.68 | 2 |
| 6. | Site clearance of obstructions | 0.9 | 3.64 | 0.68 | 0 |
| 7. | Availability of materials required | 0.9 | 3.56 | 0.66 | 2 |
| 8. | Experience in similar projects | 0.74 | 3.61 | 0.64 | 2 |
| 9. | Availability of equipment required | 0.84 | 3.40 | 0.64 | 0 |
| 10. | Proportion that could be constructed mechanically | 0.72 | 3.05 | 0.64 | 0 |
| 11. | Availability of Skilled labour | 0.83 | 3.25 | 0.58 | 0 |
| 12. | Sufficiency of the project duration | 0.79 | 3.02 | 0.56 | 0 |
| 13, | Site accessibility | 1.03 | 3.00 | 0.54 | 0 |
| 14. | Favourability of the expected cash flow | 1.08 | 2.80 | 0.47 | 0 |
| 15. | Degree of buildability | 1.11 | 2.28 | 0.47 | 0 |
| 16. | Confidence in the cost estimate | 0.73 | 3.85 | 0.45 | 0 |

**Table 2b:** Discouraging bidding factors in descending order of importance

| *i* | Discouraging Factors | Standard Deviation | Bi Score | Importance Index Ib*i* | Nb*i* |
|---|---|---|---|---|---|
| 1. | Project size | 0.65 | 3.69 | 0.73 | 5 |
| 2. | Public objection | 0.75 | 2.15 | 0.68 | 2 |
| 3. | Current work load | 0.75 | 2.90 | 0.66 | 6 |
| 4. | Risks expected | 0.73 | 3.12 | 0.52 | 6 |
| 5. | Rigidity of specifications | 0.75 | 3.66 | 0.50 | 6 |
| 6. | Availability of other projects | 0.76 | 5.21 | 0.46 | 6 |

Similarly, the contribution of a discouraging factor $F_j$ is computed by the following formula:

$$C_j = Ib_j * (CA_j - B_j) \qquad (2)$$

Where:

$CA_j$: is the contractor's assessment of the Factor $F_j$ to reflect the bidding situation under consideration.

Then, the bidding index (BI) for the project under consideration is computed using the following formula:

$$BI = \sum(Ib_i * (CA_i - B_i)) - \sum(Ib_j * (CA_j - B_j)) \quad (3)$$

For $CA_i = B_i$ and $CA_j = B_j$, the bidding index will be BI = 0. That represents the mid-point case scenario where there are neither positive nor negative contributions to the "Bid" decision, i.e. the strengths of both "Bid" and "No Bid" decisions are equal.

If BI > 0, that indicates a more positive contribution to the "bid" decision and if BI < 0 that indicates a more negative contribution to this decision. In this model, the bid decision will be recommend when BI ≥ 0 and the no-bid decision will be recommended when BI < 0. Figure 3 illustrates the hierarchical structure of the proposed model and how a bidding index is produced for a new bidding situation.

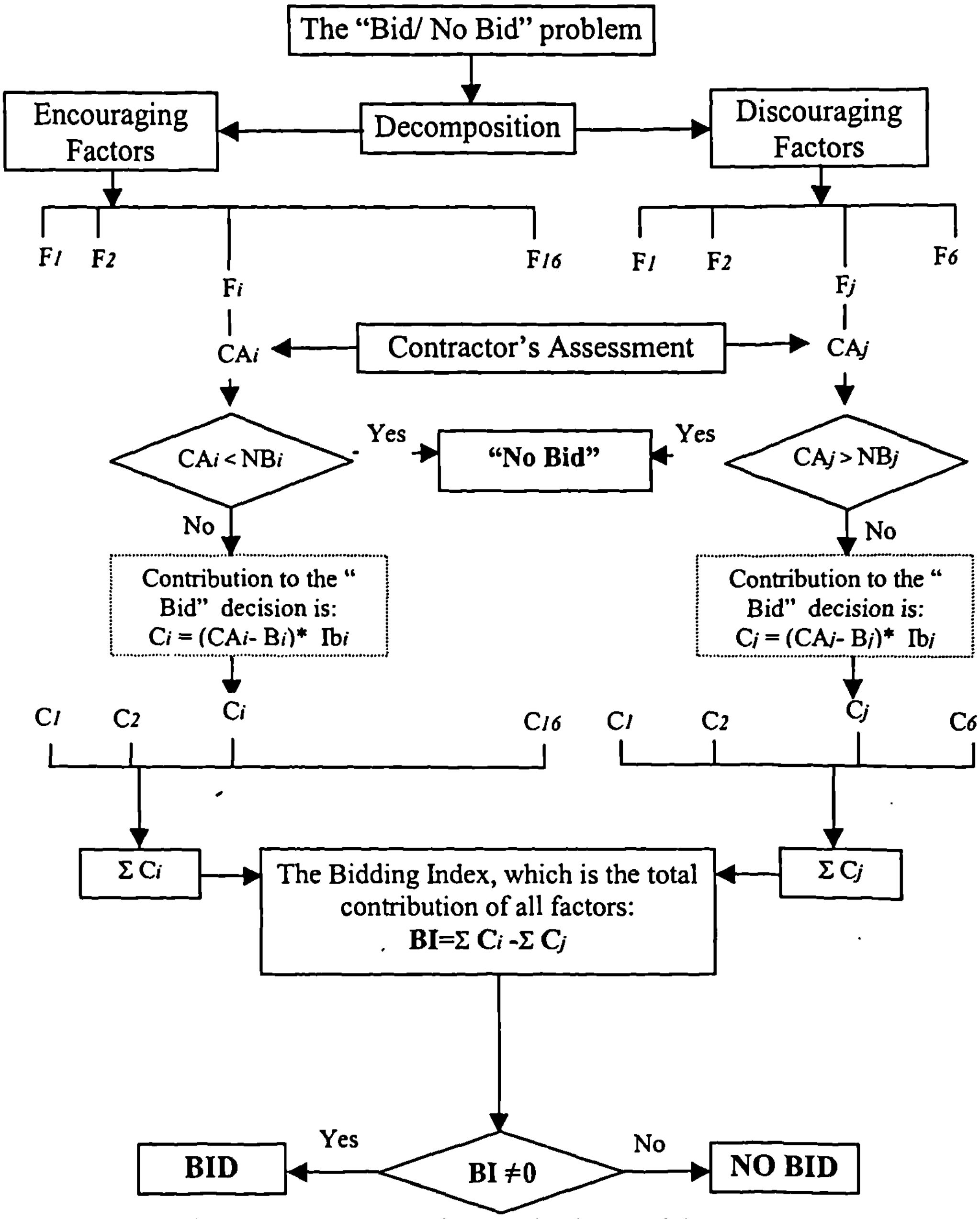


**Figure 3:** The hierarchical structure of the bid/no-bid model

## MODEL VALIDATION

This model was tested against real bidding situations. The required data were elicited using a simple form of three parts. The first part was devoted to the general characteristics of the project under consideration such as the project size, type and duration. Part two listed the most important criteria that affect the bid/no-bid decision.

The final part of the form was concerned with the final decision taken by the contractor. Three hundred copies of this form were sent to thirty general contractors operating in Syria (ten copies each). The participating contractors were requested to describe, i.e. assess each new bidding opportunity they deal with in terms of the aforementioned bidding criteria and to provide their actual bid or no bid decision.

182 forms were filled in and returned. Repetitive personal contact with the respondents was very useful to get this high response rate (61%).

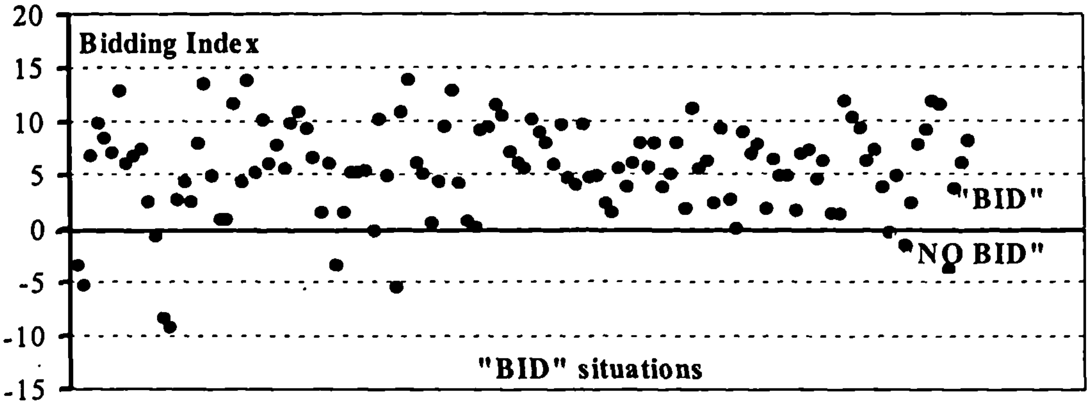


**Figure 4:** The bidding indices of real "bid" situations

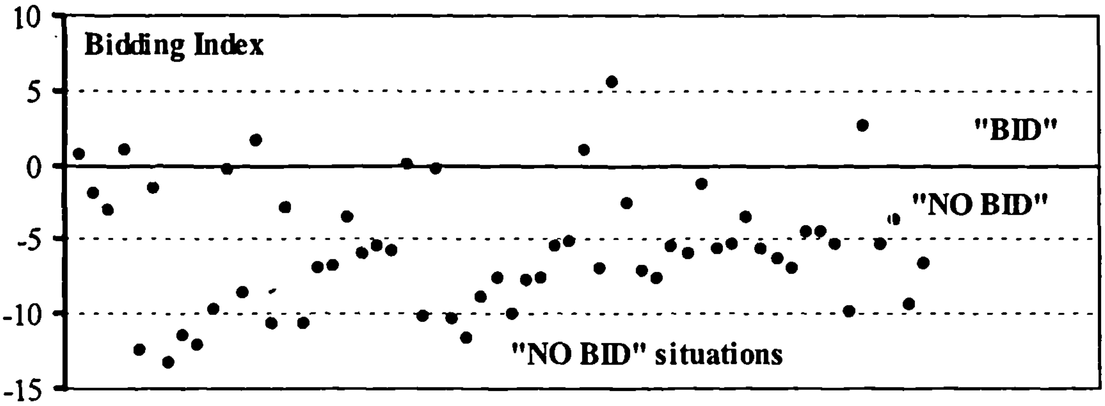


**Figure 5:** The bidding indices of real "No Bid" situations

These forms were divided into two sets; "bid" situations set which contains 124 projects and "no bid" situations set which contains 58 projects. By inputting the contractors' assessments of the first set, the model recommended to bid for 112 out of the 124 projects contained in it. Figure 4 shows the scatter diagram of the bidding indices of these "bid" situations. On the other hand, the model recommended not to bid for 51 out of the 58 projects contained in the second set as illustrated in Figure 5.

The validity of the proposed model is indicated by the following index:

$$VI = \frac{n}{N} \qquad (4)$$

Where VI is the validity index of the proposed model; n is the number of the successful simulation of the real decisions; and N is the total number of the tested cases. The model simulated successfully the contractors' decisions in (n =163) cases out of the total cases (N = 182) which implies a validity index of (VI = 90%).

In six bidding situations the model recommended not to bid while the actual decisions were to bid, however the client subsequently rejected these bids. Taking this into account improves the validity index to 93%.

# A CASE STUDY

To demonstrate the application of this model a real bidding situation was used as a case study. Table 3 presents some of the general information about the project, the contractor's assessments of the bidding situation in terms of the aforementioned criteria and the final decision to bid or not to bid on this project. A factor is assessed by a score from 0 to 6 where 0 is extremely low and 6 is extremely high.

**Table 5:** A real bidding situation

| Encouraging Factors | | | Discouraging Factors |
|---|---|---|---|
| $CA_1=6$ | $CA_7=6$ | $CA_{13}=4$ | $CA_1=4$ |
| $CA_2=4$ | $CA_8=3$ | $CA_{14}=4$ | $CA_2=2$ |
| $CA_3=4$ | $CA_9=3$ | $CA_{15}=4$ | $CA_3=4$ |
| $CA_4=4$ | $CA_{10}=5$ | $CA_{16}=4$ | $CA_4=2$ |
| $CA_5=2$ | $CA_{11}=4$ | | $CA_5=5$ |
| $CA_6=4$ | $CA_{12}=5$ | | $CA_6=3$ |

The model starts by examining the individual bidding factors. The "to-tender conditions" factor is fully met as indicated by $AC_1 = 6$. The "no bid" is not recommended in this stage because this factor does not violates its "kill" value, i.e. $AC_1 = 6 > NB_1 = 4$.

The same process is repeated for all the encouraging factors and if any one of them is scored less than its kill value $NB_i$, the model recommends a "no bid" decision but the contractor can reject the recommendation and proceed in such cases. In this bidding situation, all the encouraging factors were scored higher than their $NB_i$s.

Therefore, the model starts examining the discouraging factors. The fist one (project size) was scored $AC_1 = 4$ that means the size of this project is high compared to the average size the contractor deals with usually. However, this score is not higher than its "kill" value ($NB_1 = 5$). The other discouraging factors are examined in the same process. None exceeded its $NB_j$. Finally, the model produces a bidding index (BI) for the project under consideration: $BI = +4.78 > 0$. Therefore, the model suggests bidding for this project. In real life, the contractor submitted a bid for this project and won the contract.

# CONCLUSION

The model presented is a new method of making the bid/no-bid decision by quantifying the subjective evaluations of the bidder. The model is very flexible in the sense that attributes can be changed; some may be added and others could be deleted.

No bidding model can guarantee perfect outcomes. Nevertheless, this model is a useful tool in helping the bidder to understand the situation better and attain a reasonable degree of consistency. An overview of the past, similar models is also provided as a foundation for the proposed new model. The proposed bidding model is based on the findings of a formal questionnaire survey supported by six semi-structured interviews and validated against one hundred and eighty two real bidding situations. The model proved 93% accurate in simulating the contractors' decisions. The proposed model will be extended to enable the recommendation of a mark-up percentage, in the event of a decision to bid for a new project.

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# To bid or not to bid: a parametric solution

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One of the most important decisions that has to be made by construction companies/contractors is whether or not to bid for a new project when an invitation has been received. It would be of great help if a structured model could be developed that deals systematically with different bidding situations. A simple parametric solution for the 'bid/no bid' decision is reported in this paper. This solution is based on the findings of six semi-structured interviews and a formal questionnaire through which 38 factors that affect the bid/no bid decision were identified and ranked according to their importance to contractors operating in Syria. Only the most influential factors were considered in the development process. The model was optimized using data about 162 real bidding situations. Then the optimized model was tested using another 20 real projects. It proved 85% accurate in simulating the actual decisions. Although, the proposed model is based on data from the Syrian construction industry it could be modified very easily to suit other countries.

*Keywords*: Bid/No bid criteria, parametric bidding model, Syria

## Introduction

For any construction company, being able to deal successfully with various bidding situations is of crucial importance, especially in today's highly competitive construction market. This is the reason behind the great volume of literature concerned with bidding strategies. Since Friedman's (1956) model the literature has been flooded with many bidding models. Most of these models remained in academic circles and did not find their way into the practical world. This could be traced back to many reasons, such as: the over simplicity of the models' assumptions made them unable to represent the real-world problem; (ii) most contractors are unwilling to struggle with sophisticated mathematical models. (Ahmad and Minkarah (1988) concluded that only 11.1% of top American contractors use some sort of mathematical model. They prefer to rely on their experience in dealing with bidding situations); and (iii) most of these bidding models neglected to take into account that contractors might have other objectives rather than maximizing the expected profit. These factors imply a need for other bidding approaches. Very few researchers approached the bidding problem practically, i.e. subjectively, rather than mathematically. The former approach is more acceptable in the construction industry.

This paper reports a parametric approach for modelling the 'bid/no bid' decision-making process. Six semi-structured interviews were conducted among expert contractors, who explained how they make the bid/no bid decision in practice. Through a questionnaire survey, the main factors that influence this decision were identified and ranked according to their importance to contractors operating in Syria. Only the most influential 17 factors were considered in the final model, which was tested against 182 real bidding situations and proved 92.8% accurate in simulating the contractors' decisions. This work is part of a study being carried out to build an integrated bidding model to help Syrian contractors in making both bid/no bid and mark up size decisions.


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## Previous studies

The literature contains a great number of theoretical bidding models based on the works of Friedman (1956) and Gates (1967). All these mathematical models proved to be suitable for academia but not for practitioners. Very few qualitative approaches which study how the bidding decisions are made in practice have been carried out. Gates (1983) suggested a non-mathematical bidding strategy based on the Delphi technique, designated as the (expert subjective pragmatic estimate (ESPE)). In this model, the range and distribution of competitors' possible low bids will be estimated, and then another estimate made for the company's range and distribution of possible low bids. The two sets are then compared to select the most appropriate bid. This is done by a group of experts who, through an iterative process, will estimate the optimum bid.

Ahmad and Minkarah (1988) conducted a questionnaire survey to uncover the factors that characterize the bidding decision-making process in the United States. Subsequently, Ahmad (1990) proposed a bidding methodology based on the decision analysis technique for dealing with the bid/no bid problem. This model considers the bidding problem as a two-stage problem. One is a deterministic stage that concerns the bid/no bid decision. The important criteria considered in this stage are deterministic, i.e. certain, such as type of project and location. The second stage is probabilistic because the criteria considered in it are uncertain, such as competition and risks expected. The bidding problem is decomposed into four high level criteria and 13 lower level criteria. This model demands many inputs, some of which the bidder, especially those with limited experience, might not be able to provide. Also, it assumes that all factors contribute positively to the total worth, i.e. desirability, of the project under consideration. No distinction was made between some factors that count for the total worth, such as profitability, and others that count against the total worth, such as 'degree of hazard'. However, this approach is the most promising step on the road to modelling the bid/no bid decision.

Shash (1993) identified, through a modified version of the questionnaire used by Ahmad and Minkarah (1988), 55 factors that characterize bidding decisions in the UK. The need for work, number of competitors tendering and experience in similar projects were identified as the top three factors that affect the bid/no bid decision.

Ahuja and Arunachalam (1984) proposed a model to aid contractors in evaluating systematically the risk due to the uncertainty of availability of the required resources before bidding on a new project. As argued by Ahuja and Arunachalam, it is vital for contractors to use their own resources optimally by procuring new projects to employ resources that will be released progressively from ongoing projects. A CPM summary network, with resource allocation, is required for this model. The model tries to help contractors balance resources owned, resources available from ongoing projects, and resources which must be procured. For each alternative, the model produces a duration and cost estimate for the project. In fact, this model could be viewed as a resource allocation model and not as a bid/no bid model. It does not have clear criteria to result in a bid or no bid recommendation. Resources, and risks related to them, are not the only criteria that affect the bid/no bid decision making process.

AbouRizk *et al.* (1993) proposed an expert system called 'BidExpert'. This model was integrated with a database management program, call 'BidTrak', that retrieved historical information from past bids submitted by the company and its competitors. The user was requested to provide information about the project and the company. The information provided by the user and derived from BidTrack was then passed to BidExpert, which is linked to two external programs: the 'fair and reasonable mark up pricing model' (FaRM) and a program to calculate the accuracy of the cost estimation. BidExpert processes the outcomes using its knowledge base, and provides the user with a bid/no bid recommendation. The necessity for historical information limits the applicability of this model. BidExpert has other drawbacks. For instance, the company capacity is evaluated by the number of projects the company has handled in the last five years and the number of the current projects, without any consideration of the projects' sizes.

Abdelrazig (1995) carried out a literature review and identified 37 factors that affect the bid/no bid decision. The analytical hierarchy process (AHP) was utilized and a computer program named 'Expert Choice' was develop to help contractors in Saudi Arabia in making their bid/no bid decisions.

Wanous *et al.* (1998) conducted a questionnaire survey among Syrian contractors to uncover the parameters that characterize their bid/no bid decision-making process. 38 parameters were ranked according to their relative importance in making the bid/no bid decision in Syria. It was concluded that fulfilling the to-tender conditions, financial capability of the client, and relation with/reputation of the client are the most important factors.

## Methodology

To model the bid/no bid decision-making process it is necessary to identify the parameters that influence significant positive correlation with the actual bidding decision. Conversely, the negative factors have significant negative correlation with this decision.

## Factors influencing the bid/no bid decision

In previous work (Wanous *et al.*, 1998), 38 factors that characterize the bidding decisions were identified and ranked according to their importance to contractors operating in Syria. To avoid double counting, two of these factors (availability of qualified staff and degree of hazard) were omitted because it appears that contractors in Syria do not differentiate between them and two other factors (availability of skilled labour and risks expected). Also, the 'project geological study' factor was considered to be included in the 'risks expected' factor.

Table 1 presents the remaining 35 factors along with the importance index in making the bid/no bid decision (Ib). Factors that have less than moderate importance, i.e. Ib < 50%, in making the bid/no bid decision were discarded. The remaining factors with moderate to high importance are considered in the development of the model and are identified with an asterisk in column three of Table 1.

Table 2 presents the positive factors ranked in descending order of importance, each along with two parameters, $B_i$ and $NB_i$ where $B_i$ is a neutral score below which the factor $F_i$ will have a discouraging effect on the bid recommendation, and $NB_i$ is a kill value below which this factor will be enough to cause a no bid recommendation. Similarly, Table 3 presents the negative factors ranked in descending order of importance each along with two parameters, $B_j$ and $NB_j$, where $B_j$ is a neutral score above which the

**Table 1** Bidding factors that are considered in developing the proposed model

| Bid/no bid criteria | Ib | Factors considered to have moderate to high importance |
|---|---|---|
| Fulfilling the to-tender conditions imposed by the client | 89.88% | * |
| Financial capability of the client | 77.67% | * |
| Relations with and reputation of the client | 76.83% | * |
| Project size | 73.17% | * |
| Availability of time for tendering | 70.83% | * |
| Availability of capital required | 68.33% | * |
| Site clearance of obstructions | 68.00% | * |
| Public objection | 67.83% | * |
| Availability of materials required | 66.33% | * |
| Current work load | 65.83% | * |
| Experience in similar projects | 64.00% | * |
| Availability of equipment required | 64.00% | * |
| Method of construction (manually, mechanically) | 64.00% | * |
| Availability of skilled labour | 58.00% | * |
| Original project duration | 55.5% | * |
| Site accessibility | 53.83% | * |
| Risks expected | 52.17% | * |
| Rigidity of specifications | 50.00% | * |
| Expected project cash flow | 47.00% | |
| Degree of buildability | 47.00% | |
| Availability of other projects | 46.17% | |
| Confidence in the cost estimate | 45.33% | |
| Project location | 31.67% | |
| Original price estimated by the client | 28.50% | |
| Past profit in similar projects | 26.50% | |
| Expected date of commencing | 24.67% | |
| Availability of equipment owned by the contractor | 22.17% | |
| Expected number of competitors (degree of competition) | 17.83% | |
| Local climate | 17.50% | |
| Specific features that provide competitive advantage | 16.33% | |
| Fluctuation in labour/materials price | 15.00% | |
| Competence of the expected competitors | 12.50% | |
| Relations with other contractors and suppliers | 10.33% | |
| Proportions to be subcontracted | 5.50% | |
| Local customs | 4.17% | |

**Table 2** Parameters of the positive bidding factors

| $i$ | Positive bidding factors | $B_i$ | $NB_i$ |
|---|---|---|---|
| 1. | Fulfilling the to-tender conditions imposed by the client | 5.84 | 5 |
| 2. | Financial capability of the client | 3.48 | 2 |
| 3. | Relations with and reputation of the client | 3.84 | 2 |
| 4. | Availability of time for tendering | 2.54 | 0 |
| 5. | Availability of capital required | 3.41 | 2 |
| 6. | Site clearance of obstructions | 3.64 | 0 |
| 7. | Availability of materials required | 3.56 | 2 |
| 8. | Experience in similar projects | 3.61 | 2 |
| 9. | Availability of equipment required | 3.40 | 0 |
| 10. | Method of construction (manually, mechanically) | 3.05 | 0 |
| 11. | Availability of skilled labour | 3.25 | 0 |
| 12. | Original project duration | 3.02 | 0 |
| 13. | Site accessibility | 3.00 | 0 |

**Table 3** Parameters of the negative bidding factors

| $j$ | Negative bidding factors | $B_j$ | $NB_j$ |
|---|---|---|---|
| 1. | Project size | 3.69 | 5 |
| 2. | Public objection | 2.15 | 4 |
| 3. | Current work load | 2.90 | 6 |
| 4. | Risks expected | 3.12 | 6 |
| 5. | Rigidity of specifications | 3.66 | 6 |

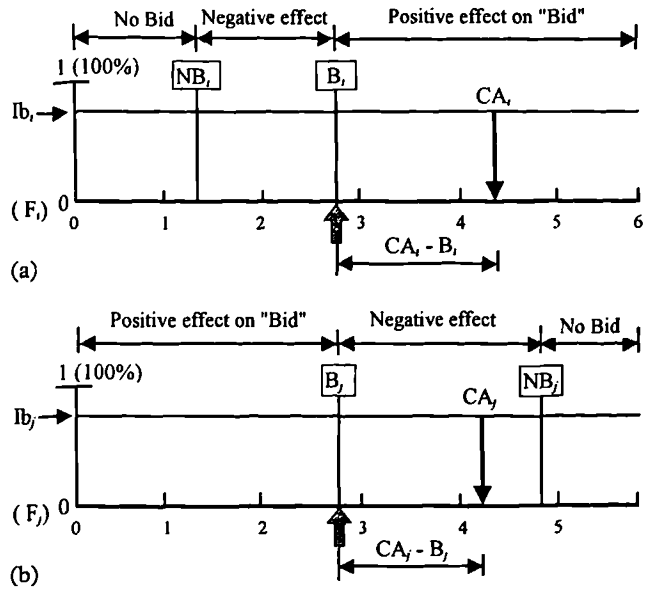


**Figure 1** A parametric model for (a) a positive factor and (b) a negative factor, where $F_i$, $F_j$ are positive, negative bidding factors, $IB_i$, $IB_j$ are importance indexes in making the bid/no bid decision, $NB_i$, $NB_j$ are kill scores of factors, $F_i$, $F_j$, $B_i$, $B_j$ are neutral scores for factors, $F_i$, $F_j$, and $CA_i$, $CA_j$, are the contractor's assessment of the bidding situation regarding factors $F_i$ and $F_j$.

factor $F_j$ will have a discouraging effect on the bid recommendation; and, $NB_j$ is a kill value above which this factor will be enough to cause no bid recommendation. The parameters $B_i$, $NB_i$, $B_j$, and $NB_j$ were selected through statistical analysis of questionnaire A and the six semi-structured interviews conducted among Syrian contractors.

## The modelling process

The bid/no bid decision-making process explained by expert Syrian contractors was translated into a systematic bidding model. First of all, a simple parametric scale was developed for each positive factor ($F_i$ in Table 2) as illustrated in Figure 1a, that explains how a positive factor affects the bid/no bid recommendation. Also, a parametric scale was developed for each negative bidding factor ($F_j$ in Table 3) as illustrated in Figure 1b, that explains how a negative factor affects this recommendation. Here, $F_i$ is a positive bidding factor; $I_i$ is the importance index of factor $F_i$; $CAi$ is the contractor's assessment (score between 0 and 6) given to $F_i$ when considering a new bidding situation; $F_j$ is a negative bidding factor; $I_j$ is the importance index of factor $F_j$; and, $CA_j$ is the contractor's assessment (score between 0 and 6) given to $F_j$ when considering a new bidding situation.

The influence of the 'Availability of materials' factor on the bid recommendation is presented graphically in Figure 2a as an example to clarify the usual effect of the classified positive factors. It is clear that this positive factor still has a negative effect if the contractor's assessment was $CA< 3.56$ (the neutral score) and that it will cause a no bid recommendation when $CA< 2$ (the 'kill' score). Also, the influence of the 'public objection' factor is illustrated in Figure 2b as an example of the negative factors. This figure shows that the 'public objection' factor still has a positive effect when $CA< 2.15$ (the neutral score). $B_i$, $NB_i$, $I_i$, $B_j$, $NB_j$ and $I_j$ were derived from information supplied by expert contractors operating in Syria, and some features of the Syrian construction industry will be reflected in these values. Therefore, this model might be of greater help to new contractors who do not have considerable experience in dealing with bidding problems. However, expert contractors can modify these values to suit their own bidding policies. Also, the basic modelling approach of the proposed model can be applied to other international industries.

It is worth mentioning that the subjective assessments $CA_i$ and $CA_j$ will be influenced by the bidder's attitude towards risk and uncertainty.

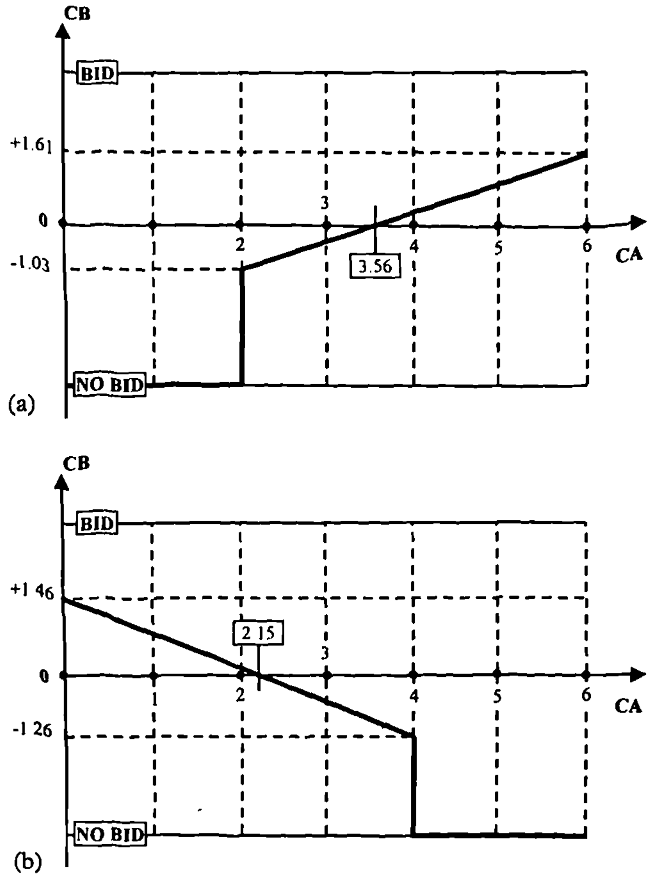


**Figure 2** Contribution of (a) 'availability of materials' factor and (b), 'public objections' factor in the Bid recommendation, where CA is the contractor's assessment and CB is the contribution to the bid recommendation

The following formula has been used to produce a bidding index ($BI_k$) for a certain project $k$.

$$BI_k = \sum_{i=1}^{m} Ib_i(CA_i - B_i) - \sum_{j=1}^{n} Ib_j(CA_j - B_j) \tag{1}$$

$BI_k$ indicates the degree of desirability of bidding on project $k$. The additivity adopted in formula 1 is justified by the small correlation between bidding attributes. This additivity has been defended by others (Ahmad, 1990).

For $CA_i = B_i$ and $CA_j = B_j$, the bidding index will be $BI_k = 0$. That represents the mid-point case scenario where there are neither positive nor negative effects on the bid decision, i.e. the strengths of both bid and no bid decisions are equal. If $BI_k > 0$, that indicates a more positive effect on the bid decision, and thus, the proposed model will recommend the bid decision when $BI_k = 0$ and the no bid decision when $BI_k < 0$.

The proposed bid/ no bid model is illustrated diagrammatically in Figure 3 and can be explained as follows

1. The user is requested to describe the bidding situation by assigning subjectively a suitable score between 0 (extremely low) and 6 (extremely high) to each positive bidding factor. In the case of any one of these factors violating its kill value, the no bid decision will be recommended. This decision could be accepted or rejected by the user.
2. Step 1 repeated for the negative factors.
3. Having all the required inputs, the model produces the bidding index ($BI_k$).
4. If $BI_k \geqslant 0$ then the bid decision is recommended.
   If $BI_k < 0$ then the no bid decision is recommended.
5. This process could be repeated for other new projects or for what-if analysis on a single project.
6. All the projects examined can be ranked in descending order according to the bidding index. This indicates which project is most suitable for the user.

To demonstrate the application of this model a case study is provided later in this paper using a real-life bidding situation.

## Sensitivity analyses

An attempt was made to simplify the proposed bidding model by reducing the number of inputs required. This should be done without affecting the model accuracy significantly. Theoretically, the least important factors should be considered for omission first. However, this strategy could be invalid because the degrees of importance of the bidding factors might not be exactly the same in real life as suggested by contractors. Also, as well as the importance index (Ib), there are other parameters ($B_i$ and $B_j$) that affect the bidding index (BI). To overcome this problem, a sensitivity index was developed for each bidding factor. For each factor, two values of the bidding index ($BI_0$ and $BI_6$) were produced for two values of the contractor's assessment (AC=0 and AC=6), while setting the other factors to the mid-case scenario (where BI=0). A sensitivity index ($SI_i$) of a bidding factor $F_i$ is defined by

$$SI_i = |BI_{0i} - BI_{6i}| \tag{2}$$

Table 4 represents $BI_0$, $BI_6$ and SI for each bidding factor, and the sensitivity of the model to changes in individual factors is illustrated in Figure 4. Factor $F_{18}$ has the lowest SI. Thus, the model was tested with factor $F_{18}$ being eliminated by using the model to produce bidding indices for 162 real bidding situations

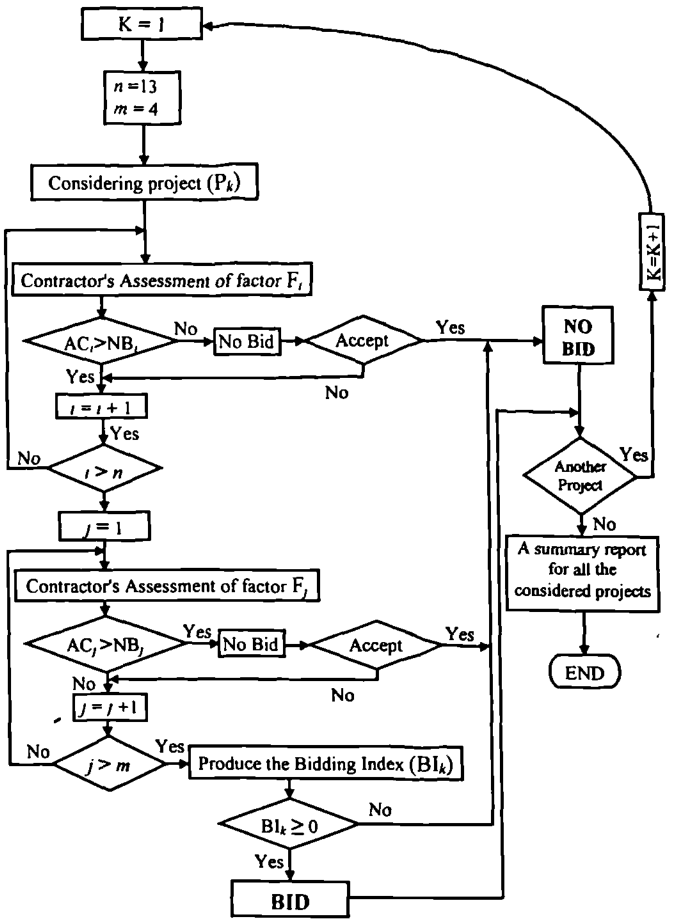


**Figure 3** Systematic model for bid/no bid decision, where K is the code of the project considered, $n$ is the number of factors ($F_i$), $m$ is the number of negative factors ($F_j$), $CA_i$ is the contractor's assessment of the bidding situation regarding factors $F_i$, $NB_i$ is the kill-score of factor $F_i$, $CA_j$ is the contractor's assessment of the bidding situation regarding factor $F_j$, and $NB_j$ is the kill-score of factor $F_j$.

**Table 4** Sensitivity of the bid/no bid decision to changes in individual factors

| $i$ | Positive bidding factors | $BI_0$ | $BI_6$ | SI $\lvert BI_0 - BI_6 \rvert$ |
|---|---|---|---|---|
| 1. | Fulfilling the to-tender conditions | −5.25 | +0.14 | 5.39 |
| 2. | Financial capability of the client | −2.70 | +1.95 | 4.65 |
| 3. | Relation with/reputation of the client | −2.95 | +1.66 | 4.61 |
| 4. | Project size | +2.70 | −1.69 | 4.39 |
| 5. | Availability of time for tendering | −1.80 | +2.45 | 4.25 |
| 6. | Availability of capital required | −2.33 | +1.77 | 4.10 |
| 7. | Site clearance of obstructions | −2.48 | +1.60 | 4.08 |
| 8. | Public objection | +1.46 | −2.61 | 4.07 |
| 9. | Availability of materials required | −2.36 | +1.62 | 3.98 |
| 10. | Current workload | +1.91 | −2.04 | 3.95 |
| 11. | Experience in similar projects | −2.31 | +1.53 | 3.84 |
| 12. | Availability of equipment required | −2.18 | +1.66 | 3.84 |
| 13. | Proportion that could be constructed mechanically | −1.95 | +1.89 | 3.84 |
| 14. | Availability of skilled labour | −1.89 | +1.60 | 3.49 |
| 15. | Sufficiency of the project duration | −1.68 | +1.68 | 3.36 |
| 16. | Site accessibility | −1.63 | +1.60 | 3.23 |
| 17. | Risks expected | +1.63 | −1.50 | 3.13 |
| 18. | Rigidity of specifications | +1.83 | −1.17 | 3.00 |

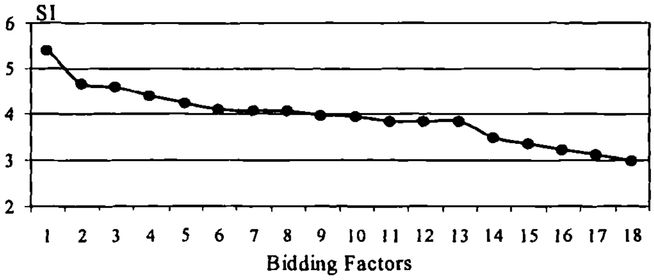


**Figure 4** Sensitivity of the bidding index to changes in individual factors, with SI the sensitivity index

**Table 5** Sensitivity to omitting some factors

| Factors omitted | No. of wrong recommendations |
|---|---|
| None | 17 |
| $F_{18}$ | 17 |
| $F_{18}+F_{17}$ | 16 |
| $F_{18}+F_{17}+F_{16}$ | 19 |
| $F_{18}+F_{17}+F_{16}+F_{15}$ | 19 |
| $F_{18}+F_{17}+F_{16}+F_{15}+F_{14}$ | 21 |

and comparing the model recommendations with the actual decisions. The model predicted the 'wrong' decision 17 cases out of 162 cases. The same process was repeated for omitting factors $F_{18}+F_{17}$, $F_{18}+F_{17}+F_{16}$, $F_{18}+F_{17}+F_{16}+F_{15}$ and $F_{18}+F_{17}+F_{16}+F_{15}+F_{14}$. Table 5 summarizes the test results. The model accuracy in simulating the actual decisions was improved marginally when omitting factors $F_{18}+F_{17}$ ('risks expected' and ' rigidity of specifications'). This indicates that these two factors are not important in practice. Therefore, these two factors were discarded. It is not necessary to discard more factors as those remaining can be assessed by the user very easily.

## Model optimization and validation

This model is based on subjective opinions elicited from Syrian contractors (through questionnaire A) and on personal experience with the Syrian construction industry. Also, some assumptions were made to facilitate the modelling process, e.g. classification of bidding factors into positive and negative. Thus, it was believed that it is necessary to optimize this model using real bidding situations.

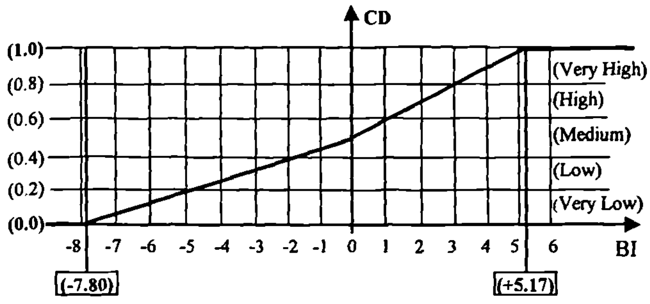


**Figure 5** Degree of confidence based on the bidding index, with BI the bidding index and CD the degree of confidence

The same 162 real bidding situations were used to optimize the proposed model and to improve the quality of its recommendations.

Initially, BI = 0 was considered as the cutoff point between bid and no bid recommendations. However, zero might not be the optimum value (X). Therefore, the model recommendations were tested against the actual decisions for different values of X, and the test results are presented in Table 6. X = 0 corresponds to the minimum number of unsuccessful recommendations indicating that it is not necessary to change the initial cutoff point (BI = 0). Two other cutoff points are required to improve the quality of the model output. These are $X_1$ and $X_2$ where: $X_1$ is the bidding index above which the model will be confident 100% in recommending to bid (or 0% in no bid), and $X_2$ is the bidding index below which the model will recommend not to bid with 100% confidence (or 0% in bid).

Based on the bidding indices produced for the previously mentioned real bidding situations, $X_1$ and $X_2$ were selected as follows: $X_1$ is the maximum bidding index below which all contractors decided not to bid ($X_1 = -7.80$); and $X_2$ is the minimum bidding index above which all contractors decided to bid ($X_2 = +5.17$). Using these values, a simple model was developed to produce the degree of confidence based on the bidding index, as illustrated in Figure 5, that can be explained as follows.

If BI ≥ 5.17, then bid recommendation with degree of confidence CDb = 100%.

If 0 ≤ BI < 5.17, then bid with degree of confidence CDb (%) = 50 + 9.7 BI.

If -7.80 < BI < 0, then 'no bid' with CDnb (%) = 50 − 6.41BI.

**Table 6** The optimum cutoff point between bid and no bid

| X | −0.15 | −0.10 | −0.05 | 0 | +0.05 | +0.10 | +0.15 |
|---|---|---|---|---|---|---|---|
| No. of unsuccessful recommendations | 17 | 17 | 16 | 16 | 16 | 16 | 17 |

If BI ≤ −7.80, then no bid with CDnb = 100%.
CDb = 100 − CDnb.

Here, CDn is the degree of confidence in a bid recommendation and CDnb is the degree of confidence in a no bid recommendation.

The final optimized model was tested against 20 real-life bidding situations that were excluded randomly from the optimization cases. The model failed to predict the actual decisions in three cases, which means the accuracy of the proposed model in simulating the actual decisions is 85%. However, to assess the reliability of this model in recommending the 'right' decisions it is necessary to know the real outcome (e.g. the actual profitability) of the real projects that were used in developing and validating it. It is intended to investigate this issue in future work.

## Cases studied

A real-life bidding situation is used to demonstrate the application of this model. The project, valued at Syrian pounds 166 million (about $4.50m) was for student accommodation. Table 7 presents the contractor's assessment of the bidding situation in terms of the aforementioned factors. Each factor was assessed using a score from 0 to 6 where 0 is extremely low and 6 is extremely high.

The model starts by examining the individual bidding factors. The 'to-tender conditions' factor is fully met, as indicated by $AC_1 = 6$. Thus, no bid is not recommended at this stage because this factor does not violates its kill value, i.e. $AC_1 = 6 > NB_1 = 4$. The same process is repeated for all the positive factors, and if any one of them is scored at less than its kill value ($NB_i$), then the model recommends a no bid decision, but the contractor can reject the recommendation and continue.

In this bidding situation, all the positive factors were scored higher than their $NB_i$. Therefore, the model starts examining the negative factors. The first one 'project size' was scored $AC_1 = 4$, which means the size of this project is high compared with the average size the contractor deals with usually. However, this score is not higher than its kill value ($NB_1 = 5$, i.e. very high). The other negative factors are examined in the same process. None exceeded its $NBj$. Finally, the model produces a bidding index (BI) for the project under consideration. In this case, the bidding index was greater than zero (BI = 4.78). Therefore, the model suggests to bid for this project. The degree of confidence in this recommendation is CD = 96% (refer to Figure 5). In real life, the contractor submitted a bid for this project and won the contract.

**Table 7** Contractor's assessment of the bidding situation

| Positive factors | | Negative factors |
|---|---|---|
| $CA_1=6$ | $CA_8=3$ | $CA_1=4$ |
| $CA_2=4$ | $CA_9=3$ | $CA_2=2$ |
| $CA_3=4$ | $CA_{10}=5$ | $CA_3=4$ |
| $CA_4=4$ | $CA_{11}=4$ | |
| $CA_5=2$ | $CA_{12}=5$ | |
| $CA_6=4$ | $CA_{13}=4$ | |
| $CA_7=6$ | | |

## Conclusion

A systematic solution for one of the most critical problems faced by construction companies/contractors is presented. An overview of previous, similar models is provided as a foundation for the proposed new model. This bidding model is based on the findings of a formal questionnaire survey supported by six semi-structured interviews and optimized using 162 real bidding situations. The model was tested against another 20 real-life projects and proved 85% accurate in simulating the actual decisions. Some bidding experience that was provided by expert Syrian contractors is embedded in this model, which could be very beneficial to new contractors who do not have considerable experience in dealing with new bidding problems. This is not offered by any other bidding models. The proposed model will be extended to make possible a recommended mark up percentage for those projects which the user decides to bid on. Although, the proposed model is based on data from the Syrian construction industry the general approach can be viewed as a universal 'shell' that can be applied to other countries.

## Acknowledgements

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# A NEURAL NETWORKS DECISION-SUPPORT SYSTEM FOR BIDDING IN CONSTRUCTION

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Abstract: One of the various strategic decisions that have to made by construction contractors is whether or not to submit a bid for a new project when an invitation has been received. An innovative neural network model is proposed in this paper to help contractors in making their bid/ no bid decisions. This model is based on one hundred and sixty two real bidding situations. The model was tested on another twenty real cases. 90% of the actual decisions of the testing sample were successfully predicted, which suggests that the model is very reliable and the ANN technique is suitable for modelling the bid/ no bid decision.

Keywords: ANN, ANN Bidding Model, "Bid/ No bid" Criteria, Construction, Syria.

## 1. INTRODUCTION

Contractors usually relay on their experience and intuitively make the bidding decisions. However, such practice does not guarantee consistent outcomes. Thus, a structured framework for making the bidding decisions can be of great help especially to new contractors who do not have considerable experience in dealing with complex bidding situations.

Recently, there has been a great interest in the implementation of expert systems (ES) and artificial neural network (ANN) techniques on various areas in the construction industry including the bidding process. The ES technology incorporates decision-support models based on heuristic if-then rules elicited from human experts. ANNs are defined as a type of information processing system whose architecture is inspired by the structure of the human brain [1]. Multi-layer perceptrons with back-propagation learning algorithm are the most commonly used ANNs. Back-propagation learning algorithm was proposed by Rumelhart *et al* [2].

The architecture of multi-layer perceptrons consists of three main components:

1. An input layer containing a set of nodes one for each input variable. These nodes do not perform any mathematical calculations. Therefore, sometimes the input layer is refereed to as the input buffer so it can be distinguished from other layers. The inputs received by this layer are forwarded to the next layer without any changes;
2. Processing elements (PEs) organised into a set of hidden layers. Each PE sums up the values received from the previous layer and uses a formula called the transfer function to produce its output, which is forwarded to all the PEs in the next layer;
3. An output layer containing a number of PEs one for each output. These PEs sum the values forwarded by the last hidden layer and apply their transfer function to produce the final outputs; and,
4. Unidirectional weighted connections between adjacent layers. The connection weights are numerical positive or negative values depending on the information being transmitted. It is by adjusting the connection weights that the ANNs learn from examples.

The communication with the outside word is through the input buffer and the output layer. The hidden layers give critical computation ability to the system [3].

Figure 1 illustrates the structure of a perceptron composed of input buffer with (n) nodes, two hidden layers containing 5 and 1 PEs respectively, and an output layer with one PE.

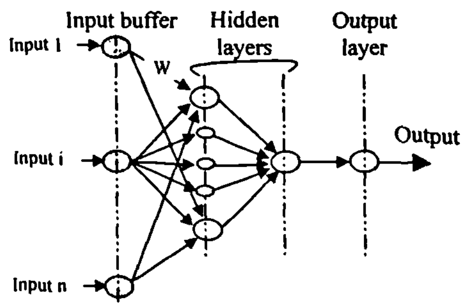


Figure 1. A multi-layer perceptron

Figure 2 illustrates a processing element with a sigmoid transfer function. Different transfer functions can be used in the same network if required.

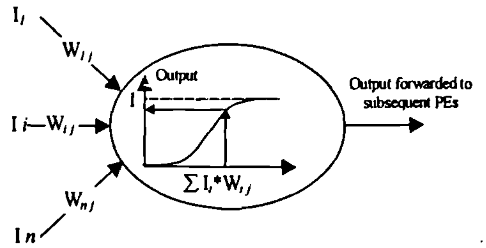


Figure 2. A processing element with a sigmiod transfer function

The development of an ANN application is an iterative trial and error process, which involves many design considerations. These include: modelling the problem under consideration, selection the number of hidden layers and their PEs, and the learning parameters. Some rules of thumb are suggested in the literature to guide this process ([4], [5]).

ANNs have been proposed by many researchers as very reliable tools for modelling unstructured problems including the mark up selection process ([4], [6]).

The present paper investigates the suitability of the ANN techniques to modelling the "bid/ no bid" decision-making process. The following section presents a brief review of the related existing bidding models.

## 2. PREVIOUS STUDIES

Numerous researchers proposed hundreds of bidding strategies, the majority of which are mathematical and statistical models concerned with estimating the probability of winning a contract with a certain mark up. The mathematical complexity of these models made them unpopular in the construction industry ([7],[1]). Recently, the bidding problem has been approached practically rather than mathematically using artificial intelligence techniques such as expert systems (ES) and artificial neural networks (ANN).

However, research continues to focus on the mark up part of the bidding process and neglects the first part although it is at least equally important. Very few publications that address the "bid/ no bid" process can be found in the construction literature.

Ahmad and Minkarah [7] conducted a questionnaire survey to uncover the factors that characterise the bidding decision-making process in the United States. Subsequently, Ahmad [9] proposed a bidding methodology based on the decision analyses technique for dealing with the "bid/ no bid" problem. This model demands many inputs some of which the bidder, especially those with limited experience, might not be able to provide. Also, it assumes that all factors contribute positively to the "bid" decision. No distinction was made between some factors that count for the "bid" decision, such as profitability, and others that count against it, such as "degree of hazard". However, this approach is the most promising step on the road of modelling the "bid/ no bid" decision.

Shash [10] identified, through a modified version of the same questionnaire used by Ahmad and Minkarah, fifty five factors that characterise the bidding decisions in the UK. The need for work, number of competitors tendering and experience in similar projects were identified as the top three factors that affect the "bid/ no bid" decision.

AbouRizk *et al* [11] proposed an expert system called BidExpert. This model retrieves historical information from past bids submitted by the company and its competitors. BidExpert uses its knowledge base and provides the user with a "bid/ no bid" recommendation. The necessity for historical information limits the applicability of this model.

Wanous *et al* [12] conducted a questionnaire survey among Syrian general contractors to uncover the factors that characterise their "bid/ no bid" decision-making process. Thirty eight factors were ranked according to their relative importance in making the "bid/ no bid" decision in Syria.

Subsequently, Wanous *et al* [13] considered the most important factors and developed a parametric profile each one. All a contractor needs when using this model is his/ her subjective assessments of the considered bidding situation in terms of certain criteria. The contractor's assessment of a certain factor is compared with its parameters to quantify the contribution of this factor in the final recommendation. Only when the accumulated contribution of all factors is positive, will a "bid" recommendation be made with an associated degree of confidence. This model was tested on twenty real bidding situations and succeeded to simulate the actual decisions of 85% of them.

Dawood [1] used expert systems to help in making the "bid / no bid" decision in the make-to-order precast industry. The explicit knowledge representation and the explanation facility are the main advantages of the ES. However, the practicality of applying this technique can be questioned because it is extremely difficult to explain the process of making the "bid/ no bid" decision through if-then rules [9].

## 3. THE DEVELOPMENT PROCESS

The development framework used in this paper can be divided into the following steps as illustrated in figure 1:

- Data elicitation and analysis;
- Initial design;
- Training;
- Testing; and,
- Adjustment;

These steps are explained in the following sections.

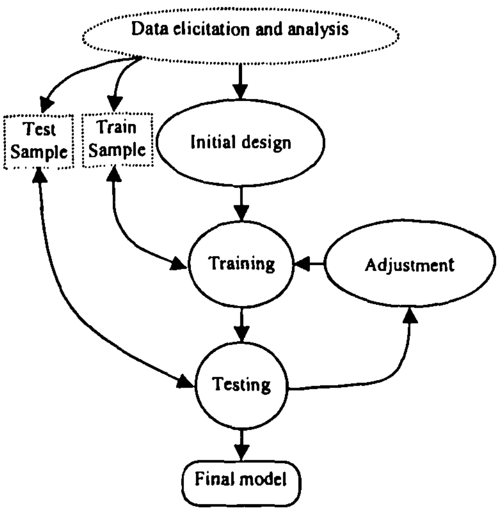


Figure 3. Framework for developing ANN models

### *3.1 Data elicitation and analysis*

The most important twenty two bidding factors identified by Wanous et al 1998 were using in designing a simple form to collect situation-outcome data on real bidding situations. The considered factors were listed in the form each with a scale from 0 to 6 where 0 represents "extremely low" and 6 represents "extremely high". Three hundred copies were sent to 30 Syrian general contractors (ten copies each). Respondents were requested to fill in a form for each bidding situation they deal with by providing their actual bid/ no bid decision and their subjective assessments of the considered bidding situation in terms of the listed factor. One hundred and eighty two forms were filled in the returned (60% response rate). The actual decisions were replaced by numerical values; "bid" with one and "no bid" with zero. Twenty cases were randomly selected and reserved for the validation process. A detailed statistical analysis was made on the remaining one hundred and sixty two cases. The cause-effect relationships between the bidding factors and the actual bid/ no bid decisions were studied through a simple correlation analysis. Factors whose correlation coefficients are greater than 0.40 were selected. The Remaining ones were omitted. Table 1 shows the considered twelve factors with their Pearson correlation coefficients (r).

### *3.2 Initial design decisions*

The factors shown in Table 1 were considered as the input variables of the initial ANN bid/ no bid model (called M1). The simplest topology was adopted for this model as a starting point. The input buffer contained twelve nodes fully connected to the output

Table 1. The most influential "bid/ no bid" factors

| Factors | r | \|r\| |
|---|---|---|
| 1. Fulfilling the to-tender conditions | +0.69 | 0.69 |
| 2. Site accessibility | +0.64 | 0.64 |
| 3. Site clearance of obstructions | +0.57 | 0.57 |
| 4. Availability of capital required | +0.52 | 0.52 |
| 5. Availability of materials required | +0.51 | 0.51 |
| 6. Proportions that could be constructed mechanically | +0.49 | 0.49 |
| 7. Confidence in the cost estimate | +0.46 | 0.46 |
| 8. Financial capability of the client | +0.44 | 0.44 |
| 9. Public objection | -0.43 | 0.43 |
| 10. Workload | -0.42 | 0.42 |
| 11. Reputation of the client | +0.42 | 0.42 |
| 12. Favourability of the cash flow | +0.41 | 0.41 |

layer, which contains only one processing element (PE) for the only output. This output is called the Neural Bidding Index (NBI). The model will make the "bid" recommendation when NBI is greater than (0.5). The closer the value of NBI is to one the more confidence in the "bid" recommendation and the closer it is to zero, the more confidence in the "no bid" recommendation. The "normalised cumulative delta" learning rule and the sigmoid transfer function were used. The other parameters were set to their default values selected by the used development software (NeuralWorks) [14]. The initial weights were automatically set to random small numbers between (-0.5) and (+0.5).

### *3.3 Training*

The back propagation learning algorithm was used to modify initial connection weights. A fixed number of training iterations (50000) was used in this stage. When the learning counter reaches this limit, the learning was automatically ceased. The ability of mode (M1) to explain the variance in the training data after 50000 iterations was presented by its training diagnostic measurements ($RMS_{train}$=0.1022 and $R^2_{train}$=0.8491). The generalisation ability of M1 after
training is tested in the following subsection.

### *3.4 Testing*

The projects reserved for the validation process were used to examine the generalisation capability of model (M1) after training. The contractors' assessments of these situations were presented to model (M1). The produced outputs were compared to the actual ones and the used software provided two measures of the test result. These measures ($RMS_{test}$ = 0.1658 and $R^2_{test}$ = 0.7983).

### *3.5 Adjustment*

In this stage the initial model was modified, i.e. fine tuned. There are endless possibilities of how the model can be modified. These include:

1. Adding hidden layer(s) and experimenting with different numbers of processing elements;

2. Examining different learning rules such as the delta rule and the cumulative delta rule;
3. Examining different transfer functions such Tangent and linear functions; and,
4. More training iterations.

After examining 57 different models, the training and testing diagnostics ($R^2$ and RMS) were improved considerably (RMS $_{train}$ = 0.0112, $R^2_{train}$ = 0.9999 and RMS $_{test}$ = 0.1522, $R^2_{test}$ = 0.8484). The structure of the corresponding model is composed of an input buffer with twelve nodes, two hidden layers with five PEs in the first one and one PE in the other, and an output layer with one PE (see Figure 1). This model was selected as the best model.

## 4. VALIDATION

In order to be accepted as a decision-support tool, the model needs to be validated. Therefore, the developed bid/ no bid model was used to predict the actual decisions of the twenty projects included in the test sample. The actual decisions were successfully predicted in eighteen cases, which means that the model is 90%' accurate in simulating the actual decisions of the test samples that have not been used in the training process. This result is very encouraging and leading to the conclusion that the ANNs technology is a suitable tool for modelling the bid/ no bid decision-making process.

## 5. CONCLUSION

This paper reviewed the "bid/ no bid" models available in the current literature and concluded that this decision has received little attention from researchers compared with the mark up part of the bidding process. The applicability of the artificial neural networks on the bid/ no bid process was investigated. Data on one hundred and sixty real-life construction projects was used to develop an innovative bid/ no bid model. The developed model was validated using another twenty real projects. It proved to be 90% accurate in simulating the actual decisions of these projects. That means the model is more accurate than a parametric model proposed in previous work [13] (see section 2). This result provides evidence that the ANN technology can be applied to the bid/ no bid process with high confidence. Although the developed model is based on data on projects from the Syrian construction industry, it provides a universal "shell" that can be applied in other countries.

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