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Neural Networks as a Tool for Modelling the Decision to Bid Process

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Neural networks and regression models are employed to model the decision to bid process. The approach demonstrates the feasibility, and usability of the neural networks as a valid tool for modelling non-linear relationships. Moreover, neural networks provide a model with the desired accuracy for the decision to bid process. The paper recommends involving the end users throughout the system development process, and creating an environment within which direct and indirect learning can be achieved by practitioners.

Key words: bidding, decision support system, construction, neural networks

INTRODUCTION

Linear regression models are tools that can be used to model the linear approximation of a problem domain. If this modelling approach is successful, it can contribute to furthering our understanding of the factors involved in decision-making, their interactions, and their contribution to the desired outcome/s.

Real life problems, however, are not linearly related. In the cases that linear approximation of a problem domain can provide acceptable accuracy for modelling, which facilitate estimation and prediction of the probable outcomes in the domain, the linear regressions as a tool would be a valid approach. Linear regression models because of their ease of use, wide spread usage which has created wide spread knowledge and awareness about their underlying concepts, and ease of visualization of the relationships are the preferred option (advantageous) in these cases.

When linear approximation of a problem domain fails to provide the desired accuracy for modelling, there is need for a tool, which is capable of modelling non-linear relationships.

The neural networks approach is such a tool, which is capable of modelling non-linear relationships with the desired accuracy. To demonstrate the feasibility and validity of this approach a neural networks Decision Support System (DSS) for the decision to bid process was developed. The related system development methodology and concepts are discussed in this paper.

Neural networks, are inspired by the functioning of the brain. They are composed of elements that perform in a manner that is analogous to biological neurons. Neural networks have learning capability, utilize numeric processing, and perform parallel distributed processing (Anderson, 1995; Wasserman, 1993; Zahedi, 1993).

The prominent feature of neural networks (Wasserman, 1993; Anderson, 1995) is their ability to learn from samples or historical data. There is no need for any explicit programming of neural network systems. Therefore, it is feasible to model the relationships between a set of inputs and a set of outputs, and develop a generalization of the relationships.

IMPORTANT FACTORS FOR DECISION TO BID

Literature related to the bidding decision process was investigated and analyzed to identify those factors that affect the decision-making process (Parvar, Lowe, Emsley, and Duff, 2000).

Initially, literature concerning the construction industry, based on primary data, was analyzed (Shash, 1993; Odusote and Fellows, 1992; Ahmad and Minkarah, 1988; Eastham, 1987), then the prescriptive and descriptive literature (The Charted Institute of Building, 1997; Thorpe and McCaffer, 1991; McCaffer and Baldwin, 1995; Smith, 1995; Skitmore, 1989; Skitmore, 1991; Kwakye, 1994; Park and Chapin, 1992; Fellow and Longford, 1980; Marsh, 1987) based on secondary data, and / or opinion of the authors, were considered. Further semi-structured and unstructured interviews with practitioners in the field, aided the development of a model. It was thought that by involving practitioners, the model would be more readily accepted by the practitioners.

Functional decomposition, to organize and classify the important factors for the decision to bid was performed. The aim of functional decomposition is to develop a conceptual view of the relationships between the factors. The decision to bid, as a function, can be decomposed to two further lower levels for analyses. The term functional decomposition or process hierarchy (Analytic Process Hierarchy) (Anderson, Sweeney, and Williams, 1997) is used to refer to this analytical approach. The lowest level is defined by the factors. The processes that assess these factors can be referred to as elementary processes. A set of these elementary processes (factors) defines a higher-level process or sub-function. The set of higher-level processes (sub-functions) define the decision to bid function.

The aim was to develop a conceptual view, which can be shared and relate to by the end users of the system, to depict relationships between factors. The important factor set, which was inclusive of the factors identified as important by the literature review, were organized to depict a model of the relationships for the decision to bid. Later, the model was validated and developed in collaboration with Henry Boot Construction Limited. The validated conceptual model is as following:

Factors and their related higher level processes

Opportunities:

1. Economic contribution of the project
2. Strategic and marketing contribution of the project
3. Competitive analyses of the tender environment
4. Feasibility of alternative design/s to reduce cost

Resources:

5. Resources to tender
6. Managerial and technical resources
7. Financial resources
8. Physical resources

Project Relations:

9. The current relationship with the project client
10. The current relationships with the project client's professional team

Project Procedures:

11. Form of contract
12. Contract conditions
13. Tendering procedure

Project Characteristics:

14. Project type
15. Project size
16. Location
17. Experience

Risks:

18. The risks involved owing to the nature of the project
19. Financial capability of the client
20. The speed of payment of the client

Competitive advantage:

21. Lowest cost

A questionnaire to assess the relevant factors for the decision to bid was devised (Appendix A). The questions function as elementary processes to elicit numeric assessment for the factors. They additionally, facilitate a systematic approach to decision making through ensuring that all relevant factors are being considered and assessed.

DATA COLLECTION AND EVALUATION

Data on the historical decision to bid were collected from a UK contractor company. Data collection was based on the developed questionnaire using a scale of one to four. 115 historical projects were assessed by the decision-makers. There were no missing values. The data set consists of 16 projects, for which the opportunity to bid was rejected, and 99 projects for which the opportunity to bid was accepted by the company.

MODELLING THE DECISION TO BID PROCESS USING REGRESSION MODELS

Several regression models to depict the relationships between the decision to bid options and the important factors were developed. Table 1 summarizes the results of the model, developed by entering all the important factors into the model. The model has the highest coefficient of determination in comparison with the other regression models generated. However, the linear regression model fails to provide sufficient accuracy for the decision model. The linear approximation of this non-linear relationships with coefficient of determination of .318 indicates that the regression model is not a valid approach and tool for modelling the decision to bid process.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Linear regression	.666	.444	.318	.2871

Table 1: Regression Model Summary

Failure of the linear model, would be an indication that perhaps non-linear relationships exist between the important factors and the decision to bid options.

To model the decision to bid process validly and effectively, a tool that can model non-linear relationships needs to be employed. Neural networks approach, which is capable of modelling non-linear relationships, was used, therefore, to model the process. The approach successfully modelled the process attaining sufficient accuracy of prediction.

THE DSS SYSTEM DEVELOPMENT APPROACH

Neural networks can be defined as a non-linear function-mapping tool, which maps the relationships between a set of input (input vector) to a set of output (output vector). The input vector consists of important factors that require due consideration and assessment for the decision making in the domain that is being modeled. The output vector represents the desired response set from the model.

A numeric assessment, on a continuous scale of 1 to 4, for 21 important factors for the decision to bid process are considered as the input vector for the DSS. Therefore, the input layer of the neural networks system, which supports the DSS, would consist of 21 nodes.

The historical decision to bid options, which were bid / no bid, were expanded to include the following four options:

1. Accept the opportunity to bid,
2. Add to a reserve list,
3. Replace with another project in the reserve list,
4. Reject the opportunity to bid.

The output layer of the neural network, therefore, consists of 4 nodes, with each node representing one of these options.

The collected data set, which consists of 115 historical projects from a contractor company in the UK, were used as training and test data sets for development of neural network systems.

The term prototyping is used to refer to the system development approach, which searches for the optimum network architecture through the development of a number of neural networks systems (prototypes), which differ in hidden layer architecture. These prototypes are then assessed for accuracy of response. A prototype that provides the desired accuracy in respect of Root Mean Square (RMS) of error and/or classification rate is then selected for further development.

The prototyping methodology was employed to search for the optimum network architecture for the neural network for the DSS for the decision to bid. The learning rule used to train the networks was the modified back-propagation learning rule (Rumelhart, McClelland, and the PDP Research Group, 1986; McClelland and Rumelhart, 1988) called Extended Delta Bar Delta (EDBD) (Minai and Williams, 1990), with the sigmoid transfer function. The optimum network architecture that was selected for further development and integration into the DSS consisted of a network with 21 nodes in the input layer, 3 hidden layers, with 15 neurons in the first hidden layer, 10 neurons in the second hidden layer, 10 neurons in the third hidden layer, and 4 nodes in the output layer. The network produced the desired accuracy in the training data and test data sets (RMS error of 0.001 and the classification rate of 100%).

DEVELOPMENT OF THE DSS USER INTERFACE

The C programming language was used to develop a user-friendly user interface with an online help facility that provides information related to the operation of the DSS.

Data entry into the system is performed through a set of dialog boxes. Each dialog elicits a numeric assessment related to a sub-set of the input variables. Online help on each dialog provides further information related to each dialog. The data entry is validated on each dialog to ensure that the numeric assessment for each factor is within range, before allowing the user to proceed to the next dialog.

The DSS recommendation is provided in a separate dialog box, which becomes active when the user requests an output. The neural network is recalled at this stage to process the input vector and the result is presented to the user. Facility for storage of information to file is also provided.

GETTING THE USERS INVOLVED

The users have been involved in the development process from the inception of the idea and throughout the development of the neural network. The input variables were generated in consultation with them, and the questionnaire and the data collection form were modified according to their feedback to ensure effective communication.

The developed neural network system, with the user-friendly interface, in addition to demonstrating the feasibility of neural networks as a DSS, enhances communication with the target users, concerning the potential and capability of neural networks.

The professionals challenged the developed system, and were pleased with the capability of the system, its accuracy and speed of response.

It is our understanding that the users' involvement in the development process created such an environment that both direct and indirect learning have been achieved by both parties involved.

The questionnaire and data collection form have been introduced as the standard procedure within the organization for the purpose of evaluating new opportunities to bid and for collecting a new data set. These evaluations, and therefore, the new data set, should be free of any bias due to the passage of time.

The new data set will be used for statistical analyses and to develop a further neural networks DSS. This DSS hopefully will be used as a standard procedure in the organization.

EXTENDED DELTA BAR DELTA (EDBD) LEARNING RULE

The back-propagation (Rumelhart, McClelland, and the PDP Research Group, 1986; McClelland and Rumelhart, 1988) learning rule is most widely used for system development in neural networks. The rule has the advantage of having the most compact representation of the problem domain. The disadvantages of requiring long training time, and theoretical possibility of getting stuck in local minima, are also mentioned in the literature.

Theoretical limitations of the back-propagation learning rule, such as getting stuck in local minima, and long training time, in fact, are not practical limitations. The problem of getting stuck in local minima can easily be remedied, and most of the time unconsciously is remedied, by starting the search from a new point in the decision space.

The term unconsciously is used to indicate, that while a neural network is being trained, its training progress is being monitored by the Root Mean Square (RMS) of error, and the classification rate. If the training is not progressing well, i.e. the classification rates are not increasing at the desired rate, and the RMS error is not decreasing at the desired rate, the system developer usually stops the training, and would make some adjustments in the learning rule's control parameters, or hidden layer architecture, and the network's weights would be initiated to a small random number before starting a new cycle of training. These actions, which are routine in system development of neural networks, would start the search for the optimum weight vector of the network, at a new point in the decision space.

The limitation of long convergence time of the back-propagation learning rule, considering the cheap processing power currently available, cannot now be considered as a practical limitation.

Also, a number of heuristics have been devised to speed up the convergence process. The momentum heuristic is one of the most effective heuristic techniques, which is widely employed in back-propagation networks.

One of the other heuristic methods to speed up the convergence process in the back propagation is the Delta Bar Delta (DBD) (Jacobs, 1988) algorithm. The DBD is based on the realization that the slope of the error surface along different weight directions might vary considerably. Since the back-propagation algorithm uses a constant learning rate for all the weights in the network, and the step size in each direction of weight space is proportional to the gradient of error with respect to the weight in each direction, the descent along different directions can vary greatly. This can cause slow descent along shallow curvature, or jumping over steep minima. The DBD addresses the issue of higher speed of convergence on the bases of four heuristics:

1. Each weight has its own learning rate.
2. The learning rates are varied based on the error surface information.
3. Learning rates are increased when the error surface gradient has the same direction for several iterations of the training. This indicates a low (shallow) curvature.
4. Learning rates are decreased when the error surface gradient has different directions for several iterations of the training. This indicates an area of high (deep) curvature.

Extended Delta Bar Delta (EDBD) (Minai and Williams, 1990) enhances the shortcomings of the DBD algorithm, for higher speed of learning. The shortcomings of the DBD algorithm that can be remedied to provide higher speed of convergence are:

- The standard DBD does not use the momentum heuristic.
- Linear increments of the learning rate, without a maximum bound, even with small rate of increment, can increase the learning rate so much that leads to divergence (wild jumps in the weight space), depending on the error surface.
- The geometrical decrement of the learning rate, some times is not sufficient to prevent the wild jumps in the weight space.

CONCLUSION AND FURTHER RESEARCH

Neural networks approach is introduced as a tool for modelling non-linear relationships. Notions of prototyping system development and getting users involved in the development process are recommended to enhance communication, further awareness of the potentials of the neural networks and to increase usability and the demand for neural network systems.

Important factors related to the decision to bid process are identified. Consideration and assessment of these factors ensure a systematic approach to the decision making process, which improves the quality of the decision making, increases productivity, and assists in achieving the strategic objectives of the organization.

Automation in the form of Decision Support Systems (DSS) can enhance these benefits further. The DSS can be based on best practices and the most productive approach to the decision-making.
Adopting the recommended methodology a neural networks DSS for the decision to bid was developed. The approach provided the benefits of improved usability and acceptability of the system, and assisted in developing a system with high accuracy of responses.

Data collection from historical projects, and the neural network system development approach adopted, in fact, acted as a feasibility study to validate the factors, the questionnaire, and the DSS development tool and methodology.

After the data were collected, further consultation meetings were held with the organization's decision makers for the decision to bid process to further refine the factors and the questionnaire. The factor related to availability of resources to tender (item 5) was replaced with two items. These are:

1. Availability of human resources to tender for the project,
2. Availability of financial resources to tender for the projects.

The questionnaire was modified accordingly.

The modified questionnaire is to form the internal procedure for the contractor company when assessing the suitability of present and future projects for the decision to bid. This set of data would be free of any bias due to time. A further DSS will be developed to model this set of data. To assess the usability of the DSS, its performance will be measured by qualitative assessment of the target users of the systems, and its contribution to productivity of the organization by a comparative evaluation of the success rate for bidding for the successful projects.

APPENDIX A: QUESTIONNAIRE

Opportunities:

1. How important is the economic (Hirschy and Pappas, 1996) contribution (profit, cash flow, and contribution to overhead) of the proposed project to the organization?
   Crucial Important Not-Important

2. Consider contribution of the project to your Strategic Intent (Hamel and Prahalad, 1989) Competency Acquisition (Prahalad and Hamel, 1990), Growth Strategy (Diversification) (Ansoff, 1957), and Communication (marketing).
   How important is the contribution of the project to the organization's strategic (Henderson, 1989), and marketing (Kotler, 1988) objectives?
   Crucial Important Not-Important

3. What is your assessment of the competitive environment of the tender and its affect on the achievement of the organizational objectives?
   Favourable Average Unfavourable

4. What is the likelihood of incorporating alternative design (cost reducing) changes?
   High Average Low

Resources:

What is your assessment of:

5. The availability of sufficient resources to tender for the project?
   High Average Low

6. The availability of the managerial and technical resources to support the implementation of the project?
   High Average Low

7. The availability of the financial resources (Brigham and Gapenski, 1994; Titard, 1996) to support the implementation of the project?
   High Average Low

8. The availability of the physical resources (plant and material) to support the implementation of the project?
   High Average Low

Project Relations:

Consider relationships in key personnel levels, in addition to the corporate level.

What is your assessment of:

9. The Current relationships with the project client?
   Favourable Average Unfavourable

10. The current relationships with the Project Client's professional team?
Favourable Average Unfavourable

Project Procedures:

What is your assessment of the appropriateness of:

11. Form of the Contract?
Favourable Acceptable Not Acceptable

12. Contract Conditions?
Favourable Acceptable Not Acceptable

13. Tendering Procedure?
Favourable Acceptable Not Acceptable

Project Characteristics:

What is your competency for management and implementation of:

14. This Project Type?
High Average Low

15. This Project Size?
High Average Low

16. The Project Location?
High Average Low

17. What is the previous experience of your organization with similar project?
High Average Low

Risks:

What is your assessment of:

18. The risks involved owing to the nature of the project?
High Average Low

19. The financial capability of the client to pay for the work carried out?
Favourable Acceptable Not Acceptable

20. The speed of payment of the client for the work carried out?
Favourable Acceptable Not Acceptable

Competitive advantage

21. How do you assess your competitive advantage (Porter, 1985) to achieve the lowest cost (Hatush and Skitmore 1997; Holt, Olomolaiye, and Harris, 1994) for the tender?
High Average Low

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