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"Examining the use of bid information in predicting contractor's performance"

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Examining the use of bid information in predicting contractor's performance

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Journal of Financial Management of Property and Construction

Research Paper

Purpose
This study examines the use bid information, including both price and non-price factors in predicting the bidder's performance.

Design/methodology/approach
The practice of the industry was first reviewed. Data on bid evaluation and performance records of the successful bids were then obtained from the Hong Kong Housing Department, the largest public housing provider in Hong Kong. This was followed by the development of a Radial Basis Function (RBF) neural network based performance prediction model.

Findings
It is found that public clients are more conscientious and include non-price factors in their bid evaluation equations. With the input variables used are information available at time of bid and the output variable is the project performance score recorded during work in progress achieved by the successful bidder, it was found that past project performance score is the most sensitive input variable in predicting future performance.

Research Limitations/Implications
This study timely reminds the inadequacy of using price alone for bid award criterion. The need of a systemic performance evaluation is also highlighted, as this information shall be highly instrumental for subsequent bid evaluations. The caveat for this study is that the prediction model was developed based on data obtained from one single source.

Originality/value
RBF neural network is used as the prediction tool because it can model non-linear function. In addition, this capability avoids tedious 'trial and error' in deciding the number of hidden layers to be used in the network model.

Keywords: Bid Evaluation, Performance records, Radial Basis Function Neural Network

INTRODUCTION

Competitive bidding is the most commonly used bidder selection practice in the construction industry. Contractor who submitted the lowest bid price among other bidders is often awarded the contract on this basis. Indeed, such practice has been regularly exercised by both public and private clients. Awarding contract to the lowest bid is particularly common for public clients because of the need to demonstrate accountability and fairness. Inevitably, bid price has been used as the sole criteria for contract award decisions. The same approach is also adopted in the private sector where financial factor is paramount. Nevertheless, the reliance on bid price alone could be problematic, as the bid price may bear no relationship to the capability of the contractor in completing the project. In order to enter the market or maintaining the work stock, some contractors, especially newly established or those from overseas, may submit suicidal low bids to attract working opportunities. As a result of insufficient budget, quality is often compromised. Worse still, claims are used to recoup the shortfall. This situation has become even more apparent in the late 90's when several major incidences involving quality issues happened in the Hong Kong construction industry. Although this cannot be determined conclusively that low bid price had attributed to this, it is undeniable that the chance of project failure is high if a contract is awarded to an incompetent contractor under the "lowest-price wins" principle. In this respect, previous studies conducted in Europe and North America pointed to the use of contractor prequalification (Hatch and Skitmore, 1998; Fong and Choi, 2000; Wong, 2004), a process that aims to screen out incompetent contractors from those prudent bidders (Cheng and Li, 2004). The metrics used for prequalification include contractors' previous experiences as well as their past performance in similar types of project (Hatch and Skitmore, 1998; Fong and Choi, 2000; Cheng and Li, 2004; Wong, 2004).

The importance of evaluating contractors' past performance in bidder selection process has been highlighted by a number of construction researchers (Alarcón and Mourgues, 2002; Kashiwagi and Byfield, 2002a-c; Kashiwagi and Savicky, 2003; Wong 2004). For example, Alarcón and Mourgues (2002) included contractors' past performance in their proposed bidder selection system after a comprehensive review of the strengths and weaknesses of the conventional contractor selection practices in U.K. Studies conducted by Ling and Liu (2004) and Wong (2004) further identified contractors' past performance as one of the criteria of selecting a competent contractor for a construction project in Singapore and U.K. respectively. In the United States, Kashiwagi and Byfield (2002a-c) sought to combat the deficiencies derived from the low-bid environment and minimize the risk of non-performance. They advocated the use of contractors' past performance as a parameter of bid evaluation. In this connection, they designed an Artificial Intelligence (AI) system called Performance Information Procurement System (PIPS) to select contractors for construction projects in the State of Utah by evaluating their past performance. Contractors selected by PIPS were reported to achieve a 99 percent success rate for completing on time, within budget, and meeting or even exceeding quality expectations. The above findings augment the importance of evaluating bidders' past performance in the bidder selection process.

Nevertheless, incorporating the contractor's past performance as a parameter of bid evaluation is no easy task. Russell and Skibniewski (1988a) described this as "an art where subjective judgement, based on an individual's experience, becomes an essential part of the process". They also pinpointed that the information required is qualitative in nature (Russell and Skibniewski, 1988b). The methods used to assess the qualitative information require a predictive judgement by the experts (Nguyen, 1985). Hatush and Skitmore (1997a) asserted that there is considerable variation in the ways to evaluate qualitative information and subjectivity may give rise to corruption and other abuses of privileges. Contractors' past performance may be difficult to be adopted as an effective bid evaluator in this connection. What is needed therefore is a quantitative, systematic and standardized approach to gauge contractors' past performance (Drew and Skitmore, 1992; Hatush and Skitmore, 1997; Holt *et al.*, 1993; Ng, 1996; Ng and Smith, 1998; Ng and Skitmore, 1994; 1995; 1999a; 1999b; Ng *et al.* 1995; 1999; Ling, 2004; Ling, *et al.* 2004).

There is no attempt to downplay the importance of considering bid price in bidder selection or suggest that the lowest bidder would definitely perform unsatisfactorily. Nevertheless, considering bid price alone during bid evaluation may import the risk of selecting an incompetent contractor who submitted a suicidal bid (Hatush and Skitmore, 1998; Alarcón and Mourgues, 2002; Wong, 2004). In this aspect, Alarcón and Mourgues (2002) pinpointed that an effective bidder selection system should comprises parameters that could foretell the successful bidder's performance in the awarded project.

This paper reports a study that aims to investigate the effectiveness of using past performance records to predict future performance of a bidder, and comparing the same with other bid information related to the bid price. The paper is organized as follows: Firstly, the process of collecting data on bid information and the contractor project performance is described. Secondly, the research methodology for investigating the prediction power of the bid information on the contractor's performance is introduced.

Thirdly, the sensitivities of the contractors' past performance, as well as the other bid information, on performance prediction are examined.

DATA COLLECTION

To accomplish the research objective of this study, the availability of data on bid information and contractors' performance is first explored. For private sector in Hong Kong, competitive bidding is still the main-stream approach of bidder selection, despite the fact that greater use of prequalification was noted in the past decade. There is generally no sophisticated system for incorporating contractors' past performance for bid evaluation purposes. For private sector developers who mainly build once for a while, the consultant team plays an active role in recommending perspective contractors. Assessment of the past performance of the contractors is then typically based on the perceptive views of the architect and/ or the project manager. Furthermore, system for regular tracking and recording of contractors' performance during the construction stage is rarely installed. As such, developers from the private sector in Hong Kong seldom maintain contractors' performance records for future bid evaluation.

In the public sector, because of accountability in using taxpayers' money, more formalized systems for assessing and recording the contractors' performance are in placed. Contractors' performance data collected from these systems may provide invaluable feedback for bid evaluation. The support from the public client in Hong Kong in providing the contractors' performance data was thus sought. Bid information and contractors' performance data are often treated as highly confidential and hence difficult to be released. In this regard, the research team is grateful to be supported by the Hong Kong Housing Authority (HKHA) in providing valuable data for this study.

HKHA is the major provider of public housing in Hong Kong. With an aim to give due consideration to the contractors' past performance in the bidder selection process, HKHA introduced a Preferential Bid Award System (PTAS) in 1999. PTAS is a system that formalizes the approach of bid assessments. Principally, submitted bids are assessed on a common scale called Preferential Bid Score (PTS) which is the composite score of the Price Score (80%) and the Performance Score (20%) (HKHA, 2002).

The Price Score is computed by comparing a bid price with the lowest bid (See Equation 1). The performance score reflects the past performance of the contractor in the HKHA projects and is computed by Equation 2. It is derived from the Performance Assessment Scoring System (PASS) developed by the HKHA in early 90's.

Price Score (%) = 80 * (Lowest bid price among submitted bids/ Submitted bid price) *(Equation 1)*

Performance Score (%) = {[20 – (Highest PASS score among bidders – PASS score of a particular bidder)/ Highest PASS score among bidders] *20} *(Equation 2)*

In essence, PASS is a performance evaluation system. The assessments are based on a comprehensive set of pre-determined standards. Through assessing the contractor's compliance against these standards by a common scale, contractors' performance is presented as a quantitative measure called PASS score. Since PASS standardized the method of gauging the contractors' performance, the performance score assessed by PASS (described as PASS score hereafter) provides a fair and effective means of comparing the contractors' past performance in bid evaluation (HKHA, 2002). In sum, PASS score is measured by both Output Assessment and Input Assessment. The assessment components of PASS are shown in Figure 1. Elaboration of PASS is beyond the scope of this paper but details of PASS can be found in the Performance Assessment Scoring System Manual published by the HKHA (HKHA, 2002).

[Figure 1 here]

In this study, data was collected from 30 HKHA projects. Two types of information were collected from each project: (1) Bid information retrievable from the PTAS (as detailed in Table 1) and (2) Performance (in terms of PASS scores) of the successful bidders.

RESEARCH METHODOLOGY

The next step of this study is to select a tool to investigate the prediction power of the bid information on contractors' performance. In this regard, Ling *et al.* (2004) employed multiple regression analysis to examine the relationship between bid information and the project performance of the successful bidder. Nevertheless, in that study not all regression equations display good prediction power because of the relatively low coefficients of determination (R^2). This may represent the low correlation between some of the bid information and the contractors' performance. Moreover, as Ranweera *et al.* (1995) reminded, the unsatisfactory results may also be due to the inability to capture non-linear relationships between the input and output variables when multiple regression is used. They further suggested the use of Artificial Neural Networks (ANN) to improve the predictive capability of the model. ANN was found to perform better than the traditional multiple regression analysis in terms of the prediction power in the work of Lin *et al.* (2003), where the input and output variables displays non-linear relationship. In sum, ANN based prediction models offer several advantages. Firstly, ANN is able to self-organize and learn. Secondly, there is no restriction on the number of input and output variables in the prediction model. Thirdly, ANN does not require linear relationships among variables thus eliminating the need to shape the approximate function before training. This accords greater flexibility in model building (Kim *et al.*, 2004). Indeed, ANN has been identified as a 'powerful modeling tool that supports decision making in construction companies at both project and corporate management levels' (Dikmen and Birgonul, 2004). ANN has been successfully applied in construction research like estimation of building quantities, activity duration as well as productivity (Bhokha and Ogunlana, 1999; Shi, 1999; Cheung *et al.*, 2000; Dikmen and Birgonul, 2004; Dikmen *et al.*, 2005). Furthermore, successful application of ANN was also reported in bid evaluation studies conducted by Hanna *et al.* (1997).

Among the various types of ANN, Multilayer Perceptron (MLP) and Radial Basis Function (RBF) are the most commonly used predictive neural network models (Lin *et al.*, 2003; NeuroDimension, 2004). However, previous studies had also identified a number of advantages of RBF over MLP neural networks. Firstly, RBF neural network training is faster, simpler, generates less standard error and requires fewer training samples than the MLP neural network. Secondly, RBF neural network can model any nonlinear function using a single hidden layer. This removes tedious trial-and-error procedures in design-decisions about the number of hidden layers (Statsoft, 2004). This study employed the RBF neural network to examine the prediction power of the bid information on the performance of the successful bidder.

Identifying RBF neural network model

The architecture of the RBF neural network model in this study is presented in Figure 2.

[Figure 2 here]

The model consists of the input variable, hidden and the output variable layers. In this study, the bid information of the successful bidder (i.e. the information as summarized in Table 1) were used as the input variables and the bidder's PASS score attained during work in progress was used the output variable. The hidden layer placed between the input and output variable layers is where the basis functions operate to intervene between the input parameters and the network output (Lin *et al.*, 2003). It is crucial to note that the number of neurons included in the hidden layer has considerable influence on the network performance. If the number of neurons is increased, the larger number of network connections resulted may encourage memorizing rather than true learning. On the other hand, the network learning performance will deteriorate with decreasing neuron numbers. Nevertheless, there is no hard and fast rule to determine the number of neurons to be included for developing the most effective RBF neural network model (i.e. a model that can deliver the most accurate prediction results (Dikmen and Birgonul, 2004; Kim *et al.* 2004). Dikmen and Birgonul (2004) suggested identifying the most effective RBF neural network model among others by evaluating their Root Means Square Error (RMSE) values calculated by the following formula (Dikmen and Birgonul, 2004; Serhatlioglu *et al.*, 2003):

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{P} \sum_{i=1}^{N} (d_{ij} - y_{ij})^2}{\text{NP}}}$$

(Equation 3)

Where

P = Number of output variables

N = Number of cases for analysis

y_{ij} = Network output for case *i* at output variable *j*

d_{ij} = Actual output for case *i* at output variable *j*

RMSE is the measure of the deviations between the actual and the predicted values of the output variable. The smaller the value of the RMSE, the more accurate the output variable value (i.e. the PASS score of the successful bidder) predicted by the RBF neural network model. Regarding this approach, Kim *et al.* (2004) suggested to test the networks with different hidden neurons ranged from 0.5* to 3* input variables. This study adopted the approach suggested by Kim *et al.* (2004) and analyzed the prediction performance of the RBF neural network model with hidden neurons ranged from 3 (i.e. 0.5* 6 input variables) to 18 (i.e. 3* 6 input variables). The model with the lowest RMSE value was consequently be selected for prediction of the successful bidders' PASS scores.

A computer package called NeuroSolutions for Excel Release 4.3 was used for the RBF neural network analysis. There are five major steps of using the collected data to train the RBF neural networks by using NeuroSolutions:

Step 1: Specify input and output variables and randomly assign the data set for training and testing the network using 'Tag data' function. In this study, data of bid information (i.e. the input variables) and the successful bidders' performance (i.e. the output variable) were obtained from 30 HKHA projects. 24 sets of the data score were randomly assigned for training the RBF neural network models that were built with different numbers of hidden neurons. They are described as the 'Training Set' hereafter. 6 sets of the data were randomly selected to form the 'Testing Set' that is used to validate the reliability of the trained network models.

Step 2: Select RBF Network in 'NeuroBuilder window', insert '3' in 'Hidden Layers' box in order to build a RBF neural network with 3 hidden neurons for analysis.

Step 3: Train the network as built in Step 2 either until the network has been trained for 500 epochs or until the means square training error becomes lower than 0.01.

Step 4: Save the network training results.

Step 5: Repeat Steps 1 to 4, yet building the RBF neural networks with 4 to 18 hidden neurons.

Evaluating the prediction results obtained from the identified model

To test the effectiveness of the bid information in predicting the successful bidders' PASS score using the identified RBF neural network model, the percentage errors of PASS score prediction were calculated using the following formula:

Percentage Error (%) = (Predicted PASS score – Actual Pass Score)/ Actual PASS score * 100% *(Equation 4)*

After consulting the designer and the user of the PASS and PTAS (i.e. the HKHA), a percentage error of 5% was used as the demarcation. That means if the difference between the predicted and the actual PASS score is within 5% (both positive and negative); the prediction result obtained is considered satisfactory.

Sensitivity testing of the bid information for predicting bidder's performance

Furthermore, the NeuroSolution package provides a function called 'Sensitivity About The Mean' that serves to indicate the contributions of the input variables towards the prediction of the output. This function expounds the cause and effect relationship between the inputs and outputs parameters of the network. In this study, the sensitivities of the various bid information (including the PTAS performance score and price score) to predict the performance of the successful bidder of the public housing projects were analyzed. The input variable displaying the highest sensitivity can be identified as the most influential performance predictor.

DISCUSSIONS

Results of model selection and validation

The prediction results obtained from the RBF neural network analyses are shown in Table 2. By comparing the RMSE values the sixteen RBF neural network models, a 6-4-1 network model (i.e. a network model with 6 input variables, 4 hidden neurons and 1 output variables) is identified as the most effective in predicting the successful bidders' PASS scores. The values of the determination of coefficient (R^2) for the training and testing results are 0.899 and 0.510 respectively.

Furthermore, as the percentage errors between the Network Predicted PASS scores and the Actual PASS scores of the projects in the Testing Set are less than 3% (Table 3 refers), such relatively low prediction errors further support the predictive power of the input variables (i.e. the bid information).

[Table 2 here]

[Table 3 here]

Sensitive Input Variable in the Prediction of Performance Score

The sensitivities of different bid information to predict the successful bidders' PASS scores are then analyzed. The sensitivity analyses extracts the cause and effect relationship between the input and output parameters of the network. The network learning is disabled during this operation such that the network weights are not affected. The percentage effects that the particular bid information has on the Network Predicted PASS scores are given in Figure 3. As shown in Figure 3, among the six input variables used to predict the performance score, PTAS Performance Score is the most sensitive. The result indicates the effectiveness of assessing the bidders' past performance on determining their performance in case of successful bidding.

Despite the lowest-bid-win strategy is still the most commonly used contractor selection practice (Alarcón and Mourgues, 2002; Hatsh and Skitmore, 1998), the findings of this study indicate that bid information related to bid price is relatively less sensitive than performance record to predict the output PASS scores (i.e. the contractors' performance). This is in line with the viewpoints of Alarcón and Mourgues (2002) who suggested downplaying the dependence on bid-price and putting more emphasis on assessing past performance in contractor selection. The findings of this study do not suggest taking price off the bid evaluation equation. In fact, price score is the second most predictive variable as identified by the sensitivity analysis. Undoubtedly bid sum should be one of the major considerations in bid evaluation especially in current construction market with increasing competitiveness and instability (Fong and Choi, 2000). Bidder selection is a complex task which makes over reliance on a single factor like bid price a risky undertaking. Developers should choose bidding evaluation parameters cautiously. The findings of this study indicate that the contractors' past performance can be one of the bid evaluators that the developers can entrust to select contractors in bid selection. The PTAS and PASS used by HKHA are good examples of how bidders' information and performance records can be kept. These are importance when it is necessary to assess them in bid evaluations. This study provides a prediction method that can incorporate non-price factors for bid evaluation purposes.

Nevertheless, the small number of data set remains the major limitation of this study. The second limitation of this study relates to the source of the data. This study uses bid information in Hong Kong public housing projects for developing the RBF neural network models. It is not clear if the same result can be obtained with data from private developers. Using greater sample size for analysis and collecting data from other countries can therefore be considered for further studies.

CONCLUSIONS

The need to consider non-price factors in bid evaluation has become more and more important with the growing number of non-performance by the lowest bidder in Hong Kong during the late 90's. Moreover, among the various non-price factors, past performance is the most indicative on the ability to complete of a bidder. In Hong Kong, public clients are more conscientious in incorporating non-price factors into the bid evaluation equation. Notably the Hong Kong Housing Authority developed the PTAS and PASS. The PTAS seeks to consider both price and non-price factors for award of contract. PASS is a comprehensive performance recording system that tracks the performance of a contractor during work in progress. A RBF neural network model is developed on the data collected from 30 housing public projects in Hong Kong. The prediction accuracy attained is within 3% and is considered satisfactory. It is further found that past performance scores is the most sensitive input variable for the prediction of future performance, followed by price scores. Such findings augmented the generally accepted view that both price and non-price factors should be considered in bid as the competence of the bidders is then evaluated (Cagno *et al*., 2001; Alarcón and Mourgues, 2002; Wong, 2004). Furthermore, the past performance data used in this study indicates the use of the robust performance recording system in construction project is invaluable not only for project management, but is also informative for future contract award exercises.

There is no doubt that clients shall have the final say in how to award a contract. It is also hard fact that the lowest-bid-win strategy is still commonly used in selection practices. There is also no attempt to generalize that the lowest bidder would not perform satisfactorily. Notwithstanding the limitations as mentioned, findings in this study reinforce the importance of considering past performance in bid evaluation.

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Bid Information	Data Description
Difference between the bid price of the successful bid and the estimated one ***[Diff btn est]***	$\frac{\text{Successful bid price - Estimated bid price by the HKHD}}{\text{Estimated bid price by the HKHD}}$ * 100%
Difference between the bid price of the successful bid and the second bid ***[Diff btn 2nd]***	$\frac{\text{Successful bid price - Second bid price}}{\text{Second bid price}}$ * 100%
% of Preliminaries of the successful bid ***[% Prelim]***	$\frac{\text{Preliminaries sum}}{\text{Total for Builder's work in the successful bid}}$ * 100%
Workload Assessment of the successful bidder ***[Wkld Assess]***	$\frac{\text{No. of unit of HKHA flats that the successful bidder is working}}{\text{Maximum No. of unit of HKHA flats that the successful bidder is permitted to build according to the statutory requirement}}$ * 100%
PTAS Price Score of the successful bidder ***[Price Score]***	$1- \frac{\text{Successful bid price - Bid price submitted by the lowest bid}}{\text{Bid price submitted by the lowest bid}}$ * 80%
PTAS Performance Score of the successful bidder ***[Perf Score]***	$1 - \frac{\text{Latest 6-month PASS score of the successful bidder}}{\text{Latest 6-month PASS score of the best performer among all bidders}}$ *20%

Table 1: Information available for bid evaluation under the PTAS

Hidden Nodes	Training RMSE				Testing RMSE			
	1st	**2nd**	**3rd**	**Average**	**1st**	**2nd**	**3rd**	**Average**
3	1.095	1.093	1.094	1.094	3.021	3.070	3.957	3.349
4	***1.116***	***1.077***	***1.089***	***1.094***	***3.024***	***2.594***	***3.034***	***2.884***
5	1.092	1.091	1.092	1.092	3.122	2.686	2.947	2.919
6	1.092	1.088	1.092	1.091	3.087	3.312	3.092	3.164
7	1.091	1.090	1.090	1.091	3.117	3.692	3.314	3.375
8	1.092	1.088	1.092	1.091	3.181	3.299	4.197	3.559
9	1.092	1.095	1.086	1.091	3.371	3.555	3.598	3.508
10	1.092	1.092	1.089	1.091	3.253	3.192	4.158	3.534
11	1.092	1.090	1.091	1.091	3.390	3.605	3.694	3.563
12	1.092	1.090	1.092	1.091	3.162	3.617	3.810	3.530
13	1.090	1.092	1.092	1.091	3.575	3.410	3.703	3.563
14	1.076	1.093	1.086	1.085	3.852	3.765	3.249	3.622
15	1.070	1.092	1.092	1.085	3.889	3.249	3.752	3.630
16	1.075	1.092	1.080	1.082	3.954	3.643	3.486	3.694
17	1.070	1.085	1.090	1.082	3.766	3.896	3.434	3.698
18	1.072	1.082	1.092	1.082	3.768	3.437	4.241	3.815

Table 2: RMSE values of the RBF neural networks with different hidden nodes

Project No.	Actual PASS Scores	Network Predicted PASS Scores	% error*	% error <1%	% error <2%	% error <3%
Training Set						
1	89.89	90.51	0.69	●	●	●
2	82.61	82.49	-0.14	●	●	●
3	91.25	90.87	-0.41	●	●	●
4	88.96	89.94	1.10		●	●
5	88.57	87.75	-0.93	●	●	●
6	85.46	84.91	-0.64	●	●	●
7	87.84	87.61	-0.26	●	●	●
8	85.88	87.46	1.84		●	●
9	90.35	88.69	-1.83		●	●
10	81.16	80.41	-0.92	●	●	●
11	89.05	88.82	-0.26	●	●	●
12	83.47	83.28	-0.23	●	●	●
13	89.14	88.85	-0.32	●	●	●
14	95.06	94.50	-0.59	●	●	●
15	91.63	90.24	-1.52		●	●
16	86.49	86.68	0.22	●	●	●
17	87.22	86.49	-0.84	●	●	●
18	90.57	89.75	-0.90	●	●	●
19	90.07	89.61	-0.52	●	●	●
20	84.86	86.17	1.55		●	●
21	83.93	83.88	-0.06	●	●	●
22	90.48	87.81	-2.95			●
23	87.43	86.54	-1.02		●	●
24	91.14	89.82	-1.45		●	●
Testing Set						
A	90.63	90.28	-0.39		●	●
B	82.61	82.73	0.14		●	●
C	86.88	84.96	-2.21			●
D	87.83	85.34	-2.84			●
E	85.08	85.51	0.50		●	●
F	93.08	90.40	-2.88			●

% error = (Actual Contractor's PASS Score - Output Contractor's PASS Scores)/ Output Contractor's PASS Scores * 100%

Table 3: Actual and Network Predicted PASS scores of training and testing projects of the prediction model developed by the 6-4-1 RBF neural networks

Performance Assessment Scoring System (PASS)

Output Assessment (70%)

This includes:

<u>Structural Works Assessment</u>

This assesses the contractor's compliance with the pre-set standards of works in:

1) Reinforcement
2) Formwork and Falsework
3) Concrete
4) Construction quality and practice

<u>Architectural Works Assessment</u>

This assesses the contractor's compliance with the pre-set standards of works in:

1) Floor Finishes
2) Internal Wall Finishes
3) External Wall Finishes
4) Ceiling Finishes
5) Windows
6) Internal Plumbing and Drainage
7) Precast Components
8) Waterproofing
9) Shop front and cladding
10) External Works
11) External Plumbing and Drainage
12) Builders' Work and Test

Input Assessment (30%)

This includes:

<u>Programme and Progress Assessment</u>

This assesses the contractor's compliance with the pre-set standards of works in:

1) Programme Arrangement
2) Progress of work
3) Mild-stone dates

<u>Management Input Assessment</u>

This assesses the contractor's compliance with the pre-set standards of works in:

1) Resources
2) Documentation
3) Coordination and Control
4) Management and Organization of Works

<u>Other Obligations Assessment</u>

This assesses the contractor's compliance with the pre-set standards of works in:

1) Site Security
2) Assess
3) Building Materials
4) Environmental, Health and Other Provisions

<u>Safety Assessment</u>

This assesses the contractor's compliance with the pre-set standards of works in:

1) General site safety;
2) Block related safety; and
3) Housing Authority Safety Auditing System

Figure 1: Assessment details of PASS

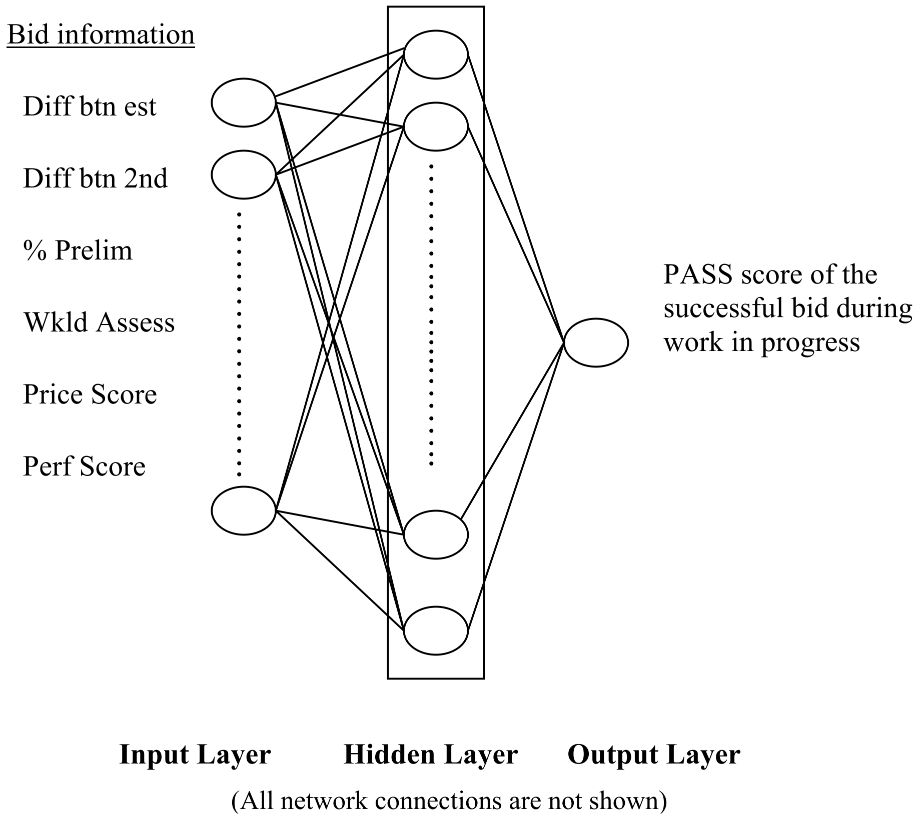

Figure 2: Network Architecture of the RBF neural network (modified from Dikmen and Birgonul, 2004)

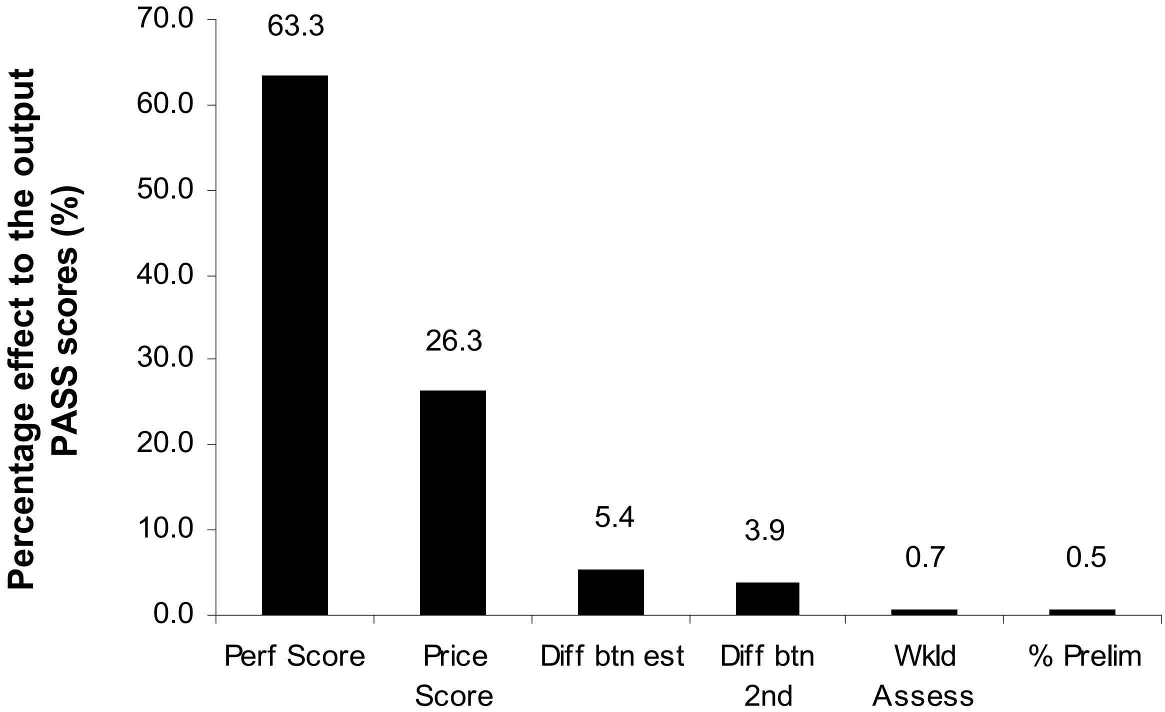

Figure 3: Sensitivity Testing Results of the prediction model developed by the 6-4-1 RBF neural networks