Creative Construction Conference 2016

Comparison of ANN and MRA Approaches to Estimate Bid Mark-Up Size in Public Construction Projects

Gul Polat[1]*, Befrin Neval Bingol[1], Asli Pelin Gurgun[2], Bulent Yel[1]

[1] Istanbul Technical University, Maslak, Istanbul, 34469, Turkey
[2] Yildiz Technical University, Istanbul, 34220, Turkey

Abstract

The intense nature of the competition in the construction industry is commonly acknowledged by professionals and researchers. Moreover, the owners commonly select the contractors based on how low they offer their bid prices and outbid their rivals. Gaining competitive advantage in order to win a contract is largely based on considering all cost components very carefully and systematically in estimating the bid price. A typical bid price consists of three main cost components, which include: direct costs (e.g., materials, equipment, labourers, etc.), indirect costs (e.g., salaries of the engineers and technical personnel, security, etc.), and bid mark-up (i.e., general overhead, profit and contingency). In the literature, various tools and techniques have been proposed for estimating bid mark-up size in construction projects. This study compares the prediction performances of the artificial neural network (ANN) and multiple regression analysis techniques (MRA). For this purpose, 52 factors that may affect the size of bid mark-up were identified and actual data of 80 public construction projects were obtained from 27 Turkish contractors in public projects in Turkey. The ANN and MRA based models were developed via MATLAB Neural Net Fitting and SPSS software programs, respectively and their prediction performances were evaluated using several statistical measures.

Keywords: Artificial neural network, bidding, mark-up, multiple regression analysis, public construction projects.

1. Introduction

Contractors predominantly win the contracts through bidding process. Since owners commonly select the contractors based on how low they offer their bid prices and outbid their rivals, contractors should be very careful when they estimate the bid price. If a contractor offers a very low bid price in order to the win the contract in a risky project environment, significant losses may occur. On the other hand, if a contractor offers a very high bid price in order to protect himself from the negative impacts of the potential risks inherent in the project, he may lose the job as the bid price in unnecessarily inflated. Therefore, a bid price should be low enough to win the contract and high enough to cover the potential losses resulted from the risks. In the construction management literature, the components of bid price are defined in several ways. According to one of the most common definition, three main components, which are; direct cost, indirect cost, and bid mark-up, constitute the bid price [1]. Direct costs include the costs of equipment, material, labour, and subcontracting, which are directly involved in the physical construction of permanent facility. On the other hand, indirect costs consist of the costs that are necessary to carry out the production (i.e., field supervision, engineers' salaries, etc.) but do not become a final part of the product. Base estimate is the sum of direct and indirect costs. Base estimate is increased by a bid mark-up, which is an estimated percentage. Bid mark-up involves there components, which are; general overhead cost, contingency, and profit. General overhead cost is the cost required to operate all business activities of a contractor (i.e., rent, utilities, etc.). Profit is the total amount of money that a contractor desires to earn from the construction project in question. Contingency, a.k.a., risk mark-up, is an amount of money allocated for possible unforeseen events that may bring about cost overruns [1-3]. The base estimate of the projects is frequently estimated nearly same by all contractors. Therefore, the bid mark-up size is the key component in bid price, which also determines winning or losing the contract in question. In other words, the right amount of bid mark-up size brings success in competitive bidding

* Corresponding author. Tel.: +902122853737; fax: +902122853737.
E-mail address: polatgu@itu.edu.tr

environment. Since the amount of the bid mark-up size is critical in winning the contract, the size of it should be determined precisely. But determining the right size of bid mark-up size is not very easy task due to the fact that it is affected by several factors, which are highly implicit and intangible [4]. Several techniques [1, 4-12] have been proposed to estimate bid mark-up size in construction projects. However, contractors still lean to estimate bid mark-up size based on their past experience and intuitions, which is highly subjective manner. This study aims to provide two useful bid mark-up size estimation tools for Turkish contractors to predict bid mark-up size in a more realistic, objective and systematic way. To achieve this goal, multiple regression analysis (MRA) and artificial neural network (ANN) methods are selected to develop the estimation models.

2. Research Methodology

The objective of the study is to generate robust estimation models for Turkish contractors that may assist them in determining bid mark-up size using MRA and ANN methods. Therefore, the following tasks were performed in this study. First, the literature was reviewed to identify the factors that may affect the bid mark-up size decision of Turkish contractors' in their bids for public projects. Then, a questionnaire was designed to obtain actual data of 80 public projects based on these identified factors. After this, the general framework of the proposed bid mark-up estimation model was constructed. The MRA and ANN methods were used to generate bid mark-up size estimation models. Finally, the performances of developed models were compared with several statistical indicators.

2.1. *Questionnaire Design*

In the light of the relevant literature [1, 3, 13-17], 52 factors that may affect the bid mark-up size decisions of the contractors were identified. These 52 factors are then categorized into 7 major groups, which are; 1) *Project Characteristics*, 2) *Economic Characteristics*, 3) *Bidding Characteristics*, 4) *Contract Characteristics*, 5) *Owner Characteristics*, 6) *Company Characteristics*, and 7) *Opportunity Characteristics* (see Table 1). In order to develop the general framework of the bid mark-up estimation model, a questionnaire including 73 questions was designed. The questionnaire has two parts. In the first part, the context of the respondent company and the project characteristics were investigated with 16 questions. In the second part, respondents evaluated the magnitudes of 52 factors on a scale consisting of five ratings such as; *very low*, *low*, *medium*, *high* and *very high* for the construction project in question.

Table 1. Factors affecting the bid mark-up size in public construction projects [4].

Major Groups and Their Constituent Factors	
MF_A Project Characteristics	
FM_{1A} : Project size	FM_{7A} : Safety problems
FM_{2A} : Project cash flow	FM_{8A} : Project type
FM_{3A} : Project's complexity	FM_{9A} : Need for new techniques and technologies
FM_{4A} : Unfavorable physical conditions of the construction site	FM_{10A} : Vagueness in the project scope
FM_{5A} : Project duration	FM_{11A} : Uncertainties in the cost estimate
FM_{6A} : Design complexities	
MF_B Economic Characteristics	
FM_{1B} : Fluctuations in material prices	FM_{3B} : Investment risks
FM_{2B} : High financing costs	
MF_C Bidding Characteristics	
FM_{1C} : Vagueness in bidding documents	FM_{4C} : Insufficient time for bid preparation
FM_{2C} : Inexperience of personnel employed in the bidding department	FM_{5C} : Size of required bonds
FM_{3C} : Awarding type	FM_{6C} : Price of the bidding documents
MF_D Contract Characteristics	
FM_{1D} : Type of contract	FM_{6D} : Vagueness of contract conditions regarding delays in payment
FM_{2D} : Owner's special requirements, which are not clearly defined in contract documents	FM_{7D} : Unclear contract conditions regarding the rights and responsibilities of the parties
FM_{3D} : Unsatisfactory contract conditions regarding design changes and additional works	FM_{8D} : Vagueness of contract conditions regarding the project time extension
FM_{4D} : Unsatisfactory contract conditions regarding claims due to additional costs arising from the geological conditions of the construction site	FM_{9D} : High taxes
FM_{5D} : Unsatisfactory contract conditions regarding escalations	

MF_E Owner Characteristics	
FM_{1E} : Financial strength of the owner	FM_{3E} : Relationship and past experience with the owner
FM_{2E} : Unsatisfactory contract conditions regarding the dispute resolution method	FM_{4E} : Unreliability of the owner
MF_F Company Characteristics	
FM_{1F} : Current work load	FM_{5F} : Problems regarding time, cost and resource planning
FM_{2F} : Level of experience in similar projects	FM_{6F} : Unavailability of qualified site engineers and managers
FM_{3F} : High turnover of the employees	FM_{7F} : Poor communication and coordination
FM_{4F} : Insufficient number of approved subcontractors	FM_{8F} : Unavailability of necessary equipment
MF_G Opportunity Characteristics	
FM_{1G} : Need for work	FM_{7G} : Potential for gaining future projects from the same owner
FM_{2G} : Number of competitors	FM_{8G} : Competition level in the market
FM_{3G} : Expertise level of competitors	FM_{9G} : Potential for gaining experience in a new construction type
FM_{4G} : Financial weakness of the company	FM_{10G} : Prestige of the project
FM_{5G} : Past bid mark-up sizes in similar projects	FM_{11G} : Project's contribution to the recognition of the company
FM_{6G} : Project's contribution to the growth of the company	

2.2. *General Framework of the Bid Mark-up Size Estimation Model*

MRA and ANN methods are used to estimate the bid mark-up size in the public projects. The bid mark-up size estimation model has seven inputs (i.e., MF_A: Project Characteristics, MF_B: Economic Characteristics, MF_C: Bidding Characteristics, MF_D: Contract Characteristics, MF_E: Owner Characteristics, MF_F: Company Characteristics, and MF_G: Opportunity Characteristics) and one output (i.e., *BM*: Bid Mark-up size). The magnitudes of the 7 major factor groups (MF_i) are used to model the function of the bid-mark-up size (*BM*). The following equation is used to express the relationship between *BM* and MF_i for each major risk group:

$$BM = f(MF_A, MF_B, MF_C, MF_D, MF_E, MF_F, MF_G) \tag{1}$$

where *BM* represent the bid mark-up as a percentage of total contract value, and MF_i represent the magnitude of each major risk group *i*, respectively. The magnitude of each major risk groups is determined as the average of the magnitudes of constituent risk factors (FM_{ji}) in each major risk group.

2.3. *Multiple Regression Analysis (MRA)*

A regression analysis is basically used to find analytical form of relation between one dependent variable and one or more independent variables [18]. Simple and multiple regression analyses (MRA) are two types of linear regression. Simple regression is used to explain variance of a dependent variable with only one independent variable. On the other hand, MRA is used when there is more than one independent variable to explain a proportion of the variance in a dependent variable at a significance level. The general form of multiple regression equation is given below (Eq. 2):

$$Y = b_0 + b_1 \times X_1 + b_2 \times X_2 + \ldots + b_n \times X_n + \varepsilon_i \tag{2}$$

where *Y* is a dependent variable (*i.e., output or criterion variable*); b_o is the constant of the regression equation; and b_1-b_n are the regression coefficients; X_1,...,X_n are independent variables (*i.e., inputs, predictor variables, explanatory variables*); and ε_i is a random error.

2.4. *Artificial Neural Network (ANN)*

ANN is a kind of computational method, which is basically inspired from the human brain. It mimics the cognitive power of human brain with artificial neurons and network to solve complex problems [19]. The nodes are the highly interconnected computational units of the system, and their role is to receive inputs and transform into output by processing them [20]. Typical ANN is composed of three layers namely, input, hidden, and output layer. The feed-forward and feed-back are two major types of architecture exist in ANN based on the connection patterns [21]. The learning mechanism of ANN depends on the architecture of the system. The learning ability of ANN provides updating the network architecture and weight of connections to work efficiently for performing special tasks. The learning algorithm is a procedure, which employs the learning rules to adjust weights during updating process. Learning from past examples is the superiority of the ANN, which also makes it desirable than the other methods [22].

3. Findings and Discussion

3.1. *Sample Characteristics*

The designed questionnaire was sent to 43 Turkish contractors, who predominantly undertake public construction projects. Only 27 respondent contractors fully completed the delivered questionnaire. Out of the 27 contractors, 8 of them have more than 40 years of experience in the construction industry and 24 of them employed more than 100 workers. The distribution of the 80 construction projects according to their types were as follows; 48.15% of them institutional and commercial building construction, 25.93% of them residential housing, 14.81 % of them heavy construction, 3.70% of them industrial construction, and 7.41% of them were other type. The contract values in the studied projects ranged between less than 50 million TL (i.e., 45.24%) to more than 250 million TL (i.e., 14.29%). In the studied projects, 78.75% of the respondents were prime contractors, 19.05% of them joint were venture member, and 2.38% of them were subcontractors. Also, only 2.38% of the contractors used basic statistical methods to estimate bid mark-up size, and the rest of them did not use any estimation methods. On the other hand, the actual bid mark-up size of the studied projects mostly ranged between 11% and 15% of the contract value.

3.2. *Development of Multiple Regression Analysis Model*

The developed multiple regression analysis model (MRAM) has six independent variables (i.e., MF_A, MF_B, MF_C, MF_D, MF_E, MF_F, and MF_G) and one dependent variable (i.e., BM). Before applying regression analysis, the correlation between inputs and output was examined and it was observed that the independent variables were highly correlated with dependent variable. After checking correlation, the multiple regression analysis was conducted via statistical package SPSS 22 in order to obtain the relationship between dependent variable and independent variables. The significance level is specified as 0.05 ($\alpha = 0.05$) for this study. The multiple regression equation was obtained based on the actual data of 80 public projects (Eq. 3). The unstandardized coefficients of parameters of regression equation and their significance level calculated and it was observed that all parameters of the model were significant at the confidence level of 95%.

$$\begin{aligned} BM = {} & 8.840 + 0.598 \times MR_A + 0.107 \times MR_B + 0.603 \times MR_C + 0.520 \times MR_D + 0.516 \times MR_E \\ & + 0.653 \times MR_F - 0.856 \times MR_G \end{aligned} \tag{3}$$

3.3. *Development of Artificial Neural Network Model*

The Neural Net Fitting application of the MATLAB was utilized to generate the bid mark-up size estimation model. The setting parameters of the artificial neural network model (ANN) were as follows: the feed-forward backpropagation network was utilized as the type of architecture; the training function was selected as Levenberg-Marquardt method; gradient-descent-with-momentum adaptation was used as the learning function of the network; the performance evaluation was determined with mean squared error (MSE) function, and tangent sigmoid (TANSIG) transfer function were selected as the activation function of the bid mark-up size estimation model. Actual data of 80 public projects were divided into three parts; 70% of them (56 projects) were used in training process, 20% of them (16 projects) were used in cross validation process, and the rest 10% of them (8 projects) were used in the testing process of the network. The number of training iteration was 1000 epochs. In order to find the best ANN model, a trial and error method based on the variation of the number of neurons in the hidden layer was performed. For that purpose, the performance of the generated models were evaluated with using several statistical indicators, which are the mean absolute percentage error (MAPE), root mean square error (RMSE), correlation coefficient (R), and coefficient of determination (R^2). Table 2 presents the performances of generated models.

Table 2. Performance indicators of ANN bid mark-up size estimation models.

	Developed models								
Performance Indicator	ANN_2	ANN_3	ANN_4	ANN_5	ANN_6	ANN_7	ANN_8	ANN_9	ANN_{10}
Number of neurons	2	3	4	5	6	7	8	9	10
MAPE (%)	2.9865	2.8231	2.7066	2.4023	6.4285	6.4012	5.0480	4.8822	4.9566
RMSE	0.4648	0.4263	0.4444	0.4583	1.1597	0.8673	0.9360	0.6925	0.8627
R	0.992	0.993	0.992	0.992	0.949	0.972	0.973	0.986	0.971
R^2	0.985	0.986	0.985	0.984	0.900	0.945	0.947	0.972	0.944

The ideal model is identified with minimum MAPE and RMSE, and maximum R and R^2, which means that MAPE and RMSE values should be close to zero, on the other side, R and R^2 values should be close to one. Based on the findings presented in Table 2, the most satisfactory model was the ANN_3, which consists of 3 neurons in the hidden layer. Therefore, ANN_3 is selected for representing artificial neural network model of this study.

3.4. *Comparison of MRA and ANN Bid Mark-up Estimation Models*

The performances of the developed models were evaluated by comparing actual bid mark-up size of 80 public construction projects with the predictions of the estimation models. Table 3 presents the actual values of the major risk groups and bid mark-up size obtained from 80 projects, and the mark-up sizes predicted by the developed MRA and ANN models. Because of the page limitations, all values of the 80 projects could not be shared in Table 3.

Table 3. Actual data for 80 public construction projects and the predictions by four multiple regression analysis models.

Project No.	Magnitude of Major Risk Groups*							Actual Bid Mark-up Size (BM) (%)	Predicted Bid Mark-up Size (BM) (%)	
	MF_A	MF_B	MF_C	MF_D	MF_E	MF_F	MF_G		MRAM	ANN_3
1	4.55	4.33	4.33	3.78	3.25	3.25	1.27	18.00	18.14	18.24
2	3.00	2.00	2.83	1.67	1.00	1.25	3.82	11.00	11.13	11.05
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
79	3.18	2.33	3.00	2.00	1.50	1.38	3.27	11.00	12.18	12.12
80	3.00	2.33	2.83	1.78	1.50	1.38	3.64	12.00	11.54	11.42

* Scale 1-5: 1= very low, 2=low, 3= medium, 4= high and 5= very high.

The performances of the proposed bid mark-up estimation models (i.e., MRAM and ANN_3) were evaluated by using the mean absolute percentage error (MAPE), root mean square error (RMSE), correlation coefficient (R), and coefficient of determination (R^2) (see Table 4).

Table 4. Performance indicators of MRA and ANN bid mark-up estimation models

Performance Indicator	Developed Models	
	MRAM	ANN_3
MAPE (%)	2.7337	2.8231
RMSE	0.4115	0.4263
R	0.993	0.993
R^2	0.987	0.986

Findings indicate that there was only slight difference between the performance of MRAM and ANN_3 bid mark-up estimation models. The MRAM has lower MAPE and RMSE and slightly higher R^2 than the ANN_3. These findings revealed that predictions of both MRAM and ANN_3 are satisfactory. Therefore, Turkish contractors can use these robust estimation models in order to predict the bid mark-up size in a more realistic, objective and systematic way for providing competitive advantage against to their rivals.

4. Conclusion

The aim of this study is to show how MRA and ANN methods can be used as a bid mark-up size estimation tool by contractors in order to make realistic predictions in a more systematic way. Therefore, two robust bid mark-up size estimation models were developed based on the data obtained form 80 public construction project that had been completed by 27 Turkish contractors. Statistical indicators were used to compare performances of the developed models. It was found that both models were satisfactory in estimating bid mark-up size. Future studies should focus on extending the proposed models via collecting more data to construct more generalized and accurate bid mark-up size estimation model.

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