Leadership in Sustainable Infrastructure
Leadership en Infrastructures Durables

Vancouver, Canada
May 31 – June 3, 2017/ *Mai 31 – Juin 3, 2017*

A DECISION TO-BID MODEL BASED ON PREDICTING THE AMOUNT OF WINNING CLAIMS USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS

Zaki, Tarek[1], Khalil, Cherif[2] and ElGindi, Mohamed[3]
[1,2,3] Graduate Student, MSc. The American University in Cairo, Egypt
[1] tarekzaki@aucegypt.edu

Abstract: Competitive bidding is one of the most commonly used bidding strategies that Clients use to procure services from Contractors. In general, a bid price is composed of main items including direct costs, indirect costs, overhead costs, profit and risk. Contractors tend to lower their bid prices as much as possible while providing competitive technical proposals in order to win bids. Due to uncertainties and price fluctuations, some Contractors consider generating profits from the amount of generated claims during the execution of the project. Hence, contractors may minimize their bidding price if they pre-estimate the amount of resolved claims during bid preparation. In this paper, a model was developed using Artificial Neural Networks (ANN) to forecast the resolved amount of claims for a specific project based on a set of parameters that affect the generated amount of claims; including: type of client, project delivery system, type of contract and contract price. Previous case studies from literature were used to train and validate the model outcomes. Genetic Algorithm (GA) was used to minimize the prediction error of the forecasted amount of claims. Using ANN reveals a promising potential for accurately predicting the expected claimed amounts. Thus, a Contractor can pre-estimate the amount of generated profit from winning claims on a specific project prior to bidding; hence, cutting-off the bidding price to increase the chances of winning the bid.

1 INTRODUCTION

The construction industry is very competitive in nature due to the presence of large numbers of highly experienced companies bidding to acquire new projects. For Contractors, bidding is considered to be one of the most commonly used techniques for acquisition of new jobs. There are two main types of bidding for projects; a Contractor could win a job either by directly negotiating with the Client or through a Competitive Bidding process [1]. Usually, most Clients prefer competitive bidding since it is considered to be an equal-opportunity method for Contractor selection. Competitive bidding is the process by which the Client selects a Contractor who is capable both technically and financially to execute the project. In this case, the Client follows a two-staged bid evaluation procedure. The first stage allows Clients to determine the Contractors that are technically capable of constructing the project; Contractors who fail the technical evaluation are disqualified and discarded. The second stage allows the Client to evaluate the financial capability of the qualified bidders from the first stage. In most cases, Clients tend to award the Contractor with the least bid price, especially if the Client was a governmental entity.

From a Contractor's perspective, the bid/no-bid decisions can be considered a dilemma which is due to a number of reasons. Not bidding for a project could be the waste of an opportunity to make a substantial profit, improve a Contractor's strength in the market, gain more relationships with Clients …etc. On the other hand, underestimating the bidding price for a project may result in large losses and the consumption of time and resources that could have been invested in more profitable projects (Bagies and Fortune 2006).

Typically, a Bid price is composed of four main elements: direct costs, indirect costs, overhead costs, profit and risk. Due to the project uncertainties, price fluctuations or Client change orders some Contractors tend to generate their profits from the amount of winning claims during the project execution phase. The decision to bid/no-bid is a very complex decision which is dependent on numerous factors. Many pricing strategies could be approached by a Contractor in order to submit a competitive winning bid.

The following section investigates the previous research on identifying the factors that affect the bid/no-bid decisions and the applications of AI in facilitating the bidding decisions.

2 LITERATURE REVIEW

2.1 Bid/or-no Bid Decisions

Freidman (1967) considered a strategy to win a bid by the maximization of the expected profit from this bid. He concluded that the bidder should select the mark-up cost that maximizes the expected value of profit. Another solution was to predict the competitors' bidding patterns by calculating ratios between their bids and cost estimates. However, what was missing in Friedman's study is the actual bid decision. Gates (1967) re-interpreted Friedman's Strategy for a single bid to a more global approach as a general applicability model for maximizing profits for bids. There were many similarities between Friedman's and Gates's approaches; however, Gates took a non-mathematical decision support model based on the Delphi technique and then reformulated the model into an economic theory for pricing construction projects. Wanous et al. (2000) re-assessed Friedman's study that aimed at developing a quantitative bidding optimization model. However, they concluded that most of Friedman's model continues to operate in academia and were not applicable in the practical world. Ahmad and Minkarah (1987) proposed a bidding methodology that was based on decision analysis techniques. The model judged the bidding problem in two stages; the first, was the deterministic stage that was concerned with whether to bid or not based on solid data such as project type and location. The second was a probabilistic stage based on uncertain data such as competition and risk expected. Rothkopf and Harstad (1994) conducted a study to determine how actual bidding decisions are made. The results concluded that most models have been concerned either with the mark-up adjustment or maximizing profit while reducing actual costs. However, no factors were concluded from the study. Bagies and Fortune (2006) extracted from literature some of the potential factors that affect the bid/no-bid decisions. The factors that influence the bidding decisions were identified and categorized into 10 groups. A summary of the factors that have influence on the bidding decisions is shown Table 1. Egemen and Mohamed (2007) investigated various factors that need to be considered by the contractors to support the decision to bid or not. They concluded that there are no specific set of factors and that the bidding decision is highly dependent on the nature of the projects.

2.2 Bidding Decisions Based on Artificial Intelligence

Other studies formulated the bidding decisions using AI such as heuristic optimization, linear regression, artificial neural networks and fuzzy logic. According to Bagies and Fortune (2006), different techniques could be used to facilitate the input of Contractors' bidding parameters to construct decision to bid models. Some of these techniques include Parametric, Artificial Neural Networks (ANN), Fuzzy Neural Networks (FNN), Fuzzy Logic, Particle Swarm Optimization, Artificial Beehive Optimization, Genetic Algorithms and Regression techniques.

Moselhi et al. (1991) developed a trial neural network for optimum mark-up estimation under different bid situations. The authors claimed that their model was able to generalize solutions and capture the probabilistic nature of the bid situations used in training. However, the data sample which was used in the training was too small to validate their model.

Table 1. Factors That Influence the Bid Decision

Category	Factor
Project Characteristics	Size of Contract Duration of The Project Type of Project Location Project Delivery System (Turnkey, Traditional, Project Management)
The Client Characteristics	Reputation Financial Capacity Entity Type (Governmental or Private)
The Contract	Type of Contract (Lump sum, Unit Price…) Ability to Alter the Contract Conditions of Contract (General and Particular)
Firms' Previous Experience	Past Experience and Profit/Loss on Similar Projects Experience in Claims Resolution
Bidding Situation	Required Bonds Values (Bid Bond, Performance Bond…) Bidding Schedule Prequalification/Bidding Requirements Terms of Payment Limits of Liability
Economic Situation	Risk Involved in Investment Availability of Labor, Plant and Materials Fluctuation of Prices Risk Customs, Taxes and Duties Risks Changes in Legislations Risks
Competition	Number of Competing Bidders Capacity of Each Competing Bidder Market Condition

Wanous et al. (2003) developed and tested a model that assists in the decision of bid/no-bid using the ANNs technique. The network consisted of 18 input nodes, 2 hidden layers and 1 output node. The model they used was based on factors derived from questionnaires which addressed the key factors that affect the bid/no-bid decision for contractors operating in Syria. The model was shown to have strong learning capabilities by a very low prediction error and its viability as a tool for modeling the decision to bid or no bid. Dikeman and Birgonul (2004) developed a neural network model to classify international projects with respect to attractiveness and competence based on the experience of Turkish contractors in overseas markets. The model was used to aid decision makers on which type of data should be collected during international business development and assists in preparing priority lists during strategic planning. Liu and Ling (2005) constructed a fuzzy logic-based ANN called Fuzzy Neural Network (FNN) to assist contractors in making mark-up decisions. The model provided users with a clear explanation to justify the viability of the estimated mark-up output. Kumar et al. (2013) presented a novel methodology based on Particle Swarm Optimization (PSO) for the preparation of optimal bidding strategies by power suppliers for industrial projects. Rivals' bidding prices have been presented as stochastic variables with probability density functions. Each participant in the model tries to maximize their profit with the help of information announced by a system operator. The simulation results showed the feasibility and robustness of the PSO approach as an efficient tool for finding the optimal bidding strategy.

3 OBJECTIVE

After reviewing the literature, it was concluded that there has been no consideration for using the amount of generated claims as a factor affecting the decision to bid; even though, claims are considered to be one of the major risks in any project that could control its success. The objective of this paper is to integrate another factor into the bidding decision which is the predicted amount of claims during the bidding stage that could be generated during the project lifecycle. The idea is to give insight to Contractors in order to minimize their bid prices based on pre-estimating the amounts of the potential claims that will occur thus increasing the chances of winning the bid and generating profit.

4 METHODOLOGY

A model was developed using ANN technique, since it is considered as a powerful prediction-based tool and useful in situations where it is difficult to formulate a relationship between different parameters. The model was developed on four stages. First, parameters that contribute to the generated amounts of claims were obtained from the literature. Second, direct interviews with experts in the construction field were conducted to examine the collected parameters from the previous stage. Third, following the interview results, the parameters were analyzed, ranked and grouped based on their impact to be used as input parameters to the ANN model and the non-significant parameters were discarded. Finally, the ANN model outputs were verified against cases extracted from the literature.

4.1 Case-Study Parameters

Parameters were collected from literature as summarized in Table 2. Then, a questionnaire was developed and distributed to a number of construction field experts through direct interviews.

4.2 Direct Interviews

A sample of 25 professionals with similar years of experience (more than 15 years) including Claim Specialists, Contract Specialists and Project Managers were interviewed. The objectives of the direct interviews were to examine the parameters that were collected from literature and their contribution to the generation of claims. Each expert was asked to qualitatively rank whether the identified parameters had Low, Medium, High contribution to the generation of claims.

4.3 Interview Analysis

The impact of each parameter collected from the direct interviews was calculated based on the following Equation 1:

$$[1]\ \text{Impact} = \sum (n_i * w_i) / n_t$$

Where n_i is the number of occurrence of an impact and w_i is the designated weight of the impact and n_t is the total number of interviewees.

The weights were organized based on scale, were the weight of the parameters low, medium and high were designated to be of equal weights = 0.33 as shown in Figure 1.

Figure 1. Impact Significance Scale

So for example, if we wish to calculate the impact of the project type parameter from the interview results, assuming that 10 interviewees defined this parameter to have a low impact, another 10 identified this parameter to have medium impact and 5 identified this parameter to have a high impact, then total impact of the parameter would be:

(10 * 0.33 + 10 * 0.66 + 5 * 0.99) / 25 = 0.54, which is MEDIUM according the scale in Figure 1.

The total results of the interviews were collected, calculated and compiled according to their significance as shown in Table 2.

Table 2. Ranked Parameters Based on Interview Results

Parameter	Impact
Project Type (Residential, Industrial, Infrastructure...etc.)	MEDIUM
Owner Type (Public, Private)	HIGH
Contract type (Unit Price, Cost Plus, Lump sum)	HIGH
Project Delivery System (PDS) (Turnkey, Traditional, Project Manager)	HIGH
Contract Condition (FIDIC, Ad-Hoc…)	MEDIUM
Original Bid Value	HIGH
Project Duration vs Scope of work	MEDIUM
Project Location	LOW
Scope of works (core and shell, renovation, MEP…etc.)	LOW

4.4 Model Design

The ANN model architecture consisted of 3 layers as shown in Figure 2. The first layer is an input layer with 4 neurons which were: Owner type (public or private), Project Delivery System (PDS) (Turnkey, Traditional or Project Manager), Contract Type (Lump Sum (LS), Unit Price (UP), Cost Plus (CP), and Original Bid Value. The second layer was a hidden layer consisting of 3 neurons. The final layer that represented the output consisted of 1 neuron which predicted the expected amount of resolved claims.

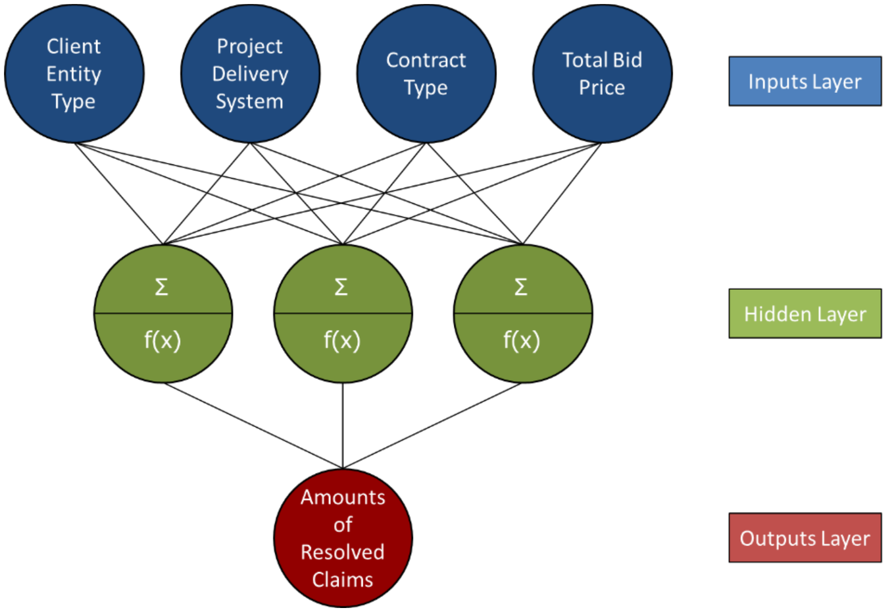

Figure 2. ANN Model Architecture

The ANN model was built on MS Excel® 2010 with a designed user interface on VBA to facilitate the user inputs where the amount of resolved claim can be predicted as shown in Figure 3.

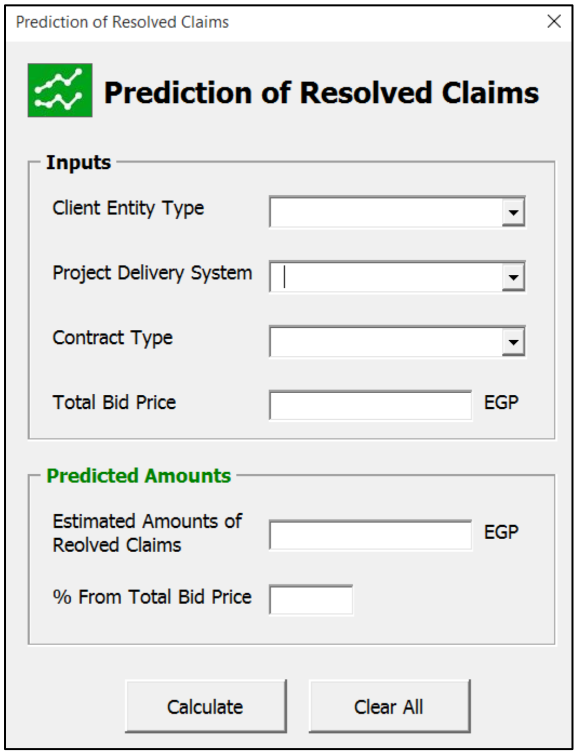

Figure 3. Model User Interface

Choosing a suitable activation function is crucial for the success and convergence of the model in a timely manner. Hyperbolic tangent “Tanh” (Figure 4) was selected in the model as some literature reviews affirm that hyperbolic tangent functions exhibit superior properties for training ANNs (Kalman and Kwasny 1992). Applying the “Tanh” function produces outputs within a range between -1 and 1.

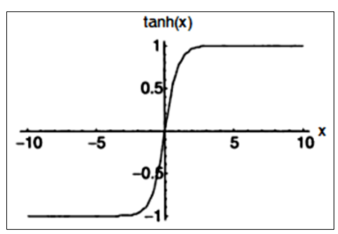

Figure 4: The Tanh activation function (Kalman and Kwasny 1992)

The network logic used was supervised learning by database previously resolved claims on projects. Randomly chosen 16 historical data sets from previous projects were extracted from a dissertation thesis (Mahmoud 2007) and used to validate the ANN model. The data were randomly split into 12 cases used for training the ANN and 4 cases were used for testing the ANN model. Figure 5 shows the raw input data of 16 cases in the model. Projects were numbered and grouped by training and testing cases.

Cat-egory	No.	Owner public / private	PDS	Contract Type	Original value EGP	Total amount of resolved claims EGP	% of resolved amounts
Training	1	Public	Turn Key	LS	13,200,000	188,000	1.42%
	2	Public	Traditional	UP	5,890,000	126,000	2.14%
	3	Private	Traditional	UP	3,000,000	48,000	1.60%
	4	Public	Traditional	Direct Order	22,500,000	222,000	0.99%
	6	Public	PM	CP	7,250,000	340,000	4.69%
	7	Public	Traditional	UP	10,000,000	398,000	3.98%
	9	Public	Traditional	UP	150,000	7,000	4.67%
	10	Public	Traditional	UP	170,000	15,000	8.82%
	11	Private	Traditional	UP	3,820,000	110,000	2.88%
	14	Private	Traditional	UP	410,000	8,000	1.95%
	15	Public	Turn Key	LS	1,150,000	48,000	4.17%
	16	Public	Traditional	UP	165,000	18,000	10.91%
Testing	5	Private	Traditional	UP	12,000,000	381,000	3.18%
	8	Public	Traditional	UP	1,025,000	46,000	4.49%
	12	Private	PM	UP	7,285,000	145,000	1.99%
	13	Private	Traditional	UP	850,000	17,000	2.00%

Figure 5: Model Database

Before proceeding with the calculations, text inputs first had to be encoded into numbers using the following Table 3.

Table 3. Text parameters encoding

Parameter			Encoding
Private	Turn Key	UP	1
Public	Traditional	LS	2
	PM	CP	3
		Direct Order	4

The second step was to normalize the numbers in the database to avoid weights to be biased towards large numbers as contributors to the overall output, which is not true. All numbers were normalized from -1 to 1 as shown in Equation 2.

[2] $NV = 2 \times (X - \min x) \div (\max x - \min x) - 1$

Where NV is the normalized value and “x” is a number in the database.

The adjustment of the prediction error was done using the back propagation method. The ANN compares its resulting outputs against the given outputs. Errors were calculated and minimized by the use of Genetic Algorithms (GA) to adjust the weights of the network. Palisade® Evolver® v5.5 add-in for MS Excel was used with an objective function to minimize the prediction error; the chromosomes (variables) were set to be the calculated weights in the hidden layer.

The error was calculated based on the sum of squares between the predicted cost from the ANN and the original actual cost from the database as shown in Equation 3.

[3] $E = (\text{Predicted Value} - \text{Original Value})^2$

The total calculation error, which was the summation of all the calculation errors per project was used as the objective function for the optimization model as shown in Figure 6.

Testing average error	0.75	Testing error	2.98
Training average error	0.11	Training error	1.33

No.	H21	FX(H11)	Desired	Sq Error
1	-0.64	-0.64	-0.91	0.07
2	-0.44	-0.44	-0.77	0.10
3	-0.76	-0.76	-0.88	0.01
4	-0.64	-0.64	-1.00	0.13
6	-0.44	-0.44	-0.25	0.04
7	-0.44	-0.44	-0.40	0.00
9	0.64	0.64	-0.26	0.81
10	0.64	0.64	0.58	0.00
11	-0.76	-0.76	-0.62	0.02
14	-0.76	-0.76	-0.81	0.00
15	-0.44	-0.44	-0.36	0.01
16	0.64	0.64	1.00	0.13
5	-0.76	-0.76	-0.56	0.04
8	0.64	0.64	-0.29	0.87
12	0.64	0.64	-0.80	2.07
13	-0.76	-0.76	-0.80	0.00

Figure 6. Error Calculation

The Evolver add-in achieved a value of 1.33 for the training squared error as the best score and 2.98 for the testing cases, after setting the stopping time to be 1 hour due to the neutralization of the convergence of the errors. The average error was calculated for the square error to check the validity of the error. The average error showed 0.11 for training cases and 0.75 for the testing which is acceptable. After assuring that the amount of prediction error was accepted, the model was put to test for verification.

5 RESULTS

The user enters the following information as shown in Figure 7. Then, the model predicts the estimated amounts of resolved claims for this project which is equal to EGP 8,435,063.47 which is equivalent to 2.28% from the original bid estimate.

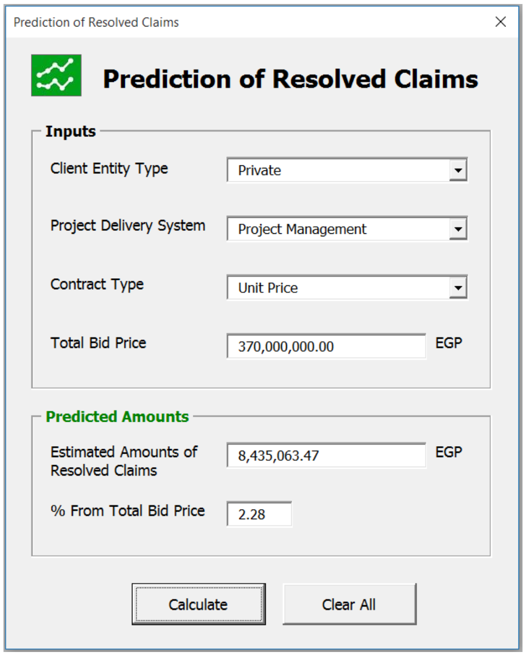

Figure 7. Model User Interface with results

In order to further validate the model accuracy, a sensitivity analysis was conducted for each input parameter by providing constant data for all parameters except the one whose sensitivity was being examined. The outputs of this analysis showed that there are factors directly affecting the amount of claims such as owner type, PDS and contract type while the original value had no effect on predicting the amount of claims as shown in Figure 8. It can be shown that the parameters generate the highest percentage of claims is when the owner type is public or when the project delivery system is PM or when the contract type is either CP or direct order.

Item	Client Entity Type	Project Delivery System	Contract Type	Total Bid Price	Total amount of Estimated solved claims	% of Estimated solved amounts
Client Entity Type	Private	Traditional	LS	2,000,000.00 EGP	EGP 153,243.11	7.66%
Client Entity Type	Public	Traditional	LS	2,000,000.00 EGP	EGP 64,938.71	3.25%
Project Delivery System	Public	Turn Key	LS	2,000,000.00 EGP	EGP 64,938.71	3.25%
Project Delivery System	Public	Traditional	LS	2,000,000.00 EGP	EGP 64,938.71	3.25%
Project Delivery System	Public	PM	LS	2,000,000.00 EGP	EGP 172,586.88	8.63%
Contract Type	Public	Turn Key	UP	2,000,000.00 EGP	EGP 64,938.71	3.25%
Contract Type	Public	Turn Key	LS	2,000,000.00 EGP	EGP 64,938.71	3.25%
Contract Type	Public	Turn Key	CP	2,000,000.00 EGP	EGP 184,147.19	9.21%
Contract Type	Public	Turn Key	Direct Order	2,000,000.00 EGP	EGP 184,147.19	9.21%
Total Bid Price	Public	Turn Key	UP	500,000.00 EGP	EGP 16,234.68	3.25%
Total Bid Price	Public	Turn Key	UP	2,000,000.00 EGP	EGP 64,938.71	3.25%
Total Bid Price	Public	Turn Key	UP	1,000,000.00 EGP	EGP 32,469.35	3.25%

Figure 8. Sensitivity Analysis Results

6 LIMITATIONS AND SUGGESTED IMPROVEMENTS

Although the model showed predicted claims values with a reasonable error, there are still some limitations that need to be considered. The data used to build the ANN was based on 16 cases only (12 for training and 4 for testing) and the used input parameters considered were 5 only and were extracted from earlier projects' history. There are other suggested factors that could considered as suggested improvements to the model to produce better forecasted results; such as increasing the number of expert interviews to identify and incorporate more parameters to the model such as the project characteristics, the Client's background history, competition with other bidders and complexity of the project. More parameters and more historical data are required to increase the accuracy.

7 CONCLUSION

The decision to bid/no-bid is a very complex decision and is dependent on numerous factors. Many pricing strategies could be approached by a Contractor in order to submit a competitive winning bid. After reviewing the literature, it was concluded that that there has been no consideration of the amount of generated claims as a factor affecting the decision to bid strategy; even though, claims are considered to be one of the major risks in any project that affects its success. The objective of this paper was to integrate the predicted amount of claims as one of the factors that affect the decision to bid. The idea was to give insight to Contractors in order to minimize their bid prices based on pre-estimating the amounts of the potential claims that will occur; thus increasing the chances of winning the bid and generating profit. A model was developed using ANN to predict the amount of winning claims. ANN technique was adopted since it has powerful prediction capabilities and useful in situations where it is difficult to formulate relationships between different parameters. The model was trained using 12 projects with their bid prices and the amounts of resolved claims and tested with 4 projects to validate the model accuracy before being used for claims prediction. GA is used to minimize the predication error and to formulate the model. Although the available historical database provided in this paper was not extensive and the number of direct interviews conducted was limited, the developed model effectively predicts the resolved amount of claims expected in a potential project. By applying the ANN model, a Contractor could identify the project parameters and the original bidding price in the model and then the predicted amount of claims could be generated. The amount of claims could give the contractor some insight about the nature of the project as well as contribute to the Contractor’s decision to bid or not to bid.

References

Ahmad, I. and Minkarah, I. A. 1987. Optimum mark-up for bidding: a preference-uncertainty trade off approach. *Civil Engineering Systems*, **4**(4):170-174

Bagies, A. and Fortune, C. 2006. Bid/no bid decision modelling for construction projects. In *Proceedings of the 22nd Annual ARCOM Conference*, pages: 511-521, UK.

Dikemen, I. and Birgonul, M. T. 2004. Neural Network Model to Support International Market Entry Decisions. *Journal of Construction Engineering and Management*, **130**(1).

Egemen, M. and Mohamed, A. N. 2007. A framework for contractors to reach strategically correct bid/no bid and mark-up size decisions. *Building and Environment*, **42**(3):1373-1385

Friedman, L. A competitive-bidding strategy 1967. *Operations research*, **4**(1):104-112.

Gates, M. Bidding strategies and probabilities 1967. *Journal of the Construction Division*, **93**(1):75-107.

Kalman, B. L. and Kwasny, S. C. 1992. Why Tanh: choosing a sigmoidal function. In *Proceedings of the International Joint Conference on neural networks IJCNN*, 578-581.

Kumar, V., Kumar D. M., Edukondalu K. 2013. Bidding Strategy Considering Risk by Generating Companies in an Open Electricity Market Using Particle Swarm Optimization, *International Journal of Energy Engineering*, **3**(1):7-11.

Liu, M. and Ling, Y. Y. Modeling a contractor’s Mark-up Estimation. *Journal of Construction Engineering and Management*, **131**(4):391-399, 2005.

Mahmoud. A. 2007. Reducing the Likelihood of Construction Disputes Using Expert System. Construction Engineering Department, Faculty of Engineering, Zagazig University.

Moselhi, O., T. Hegazy, and P. Fazio. 1991. Markup estimation using AI methodology. In *Proceedings of the 2nd International Conference on the Application of Artificial Intelligence Techniques to Civil and Structural Engineering*, pages: 255-267, Oxford, UK.

Palisade 2009. Evolver, Optimization Add-in for Microsoft Excel. Computer software.

Rothkopf, M. H. and Harstad, R. M. 1994. Modelling competitive bidding: A critical essay. *Management Science*, **40**(3):364-384, 1994.

Shash, A. A. 1993. Factors considered in tendering decisions by top UK contractors. *Construction Management and Economics*, **11**(2):111-118, 1993.

Wanous, M., Boussabaine, A. A. and Lewis, J. 2000. To bid or not to bid: a parametric solution. *Construction Management & Economics*, **18**(4):457-466.

Wanous, M., Boussabaine, H. A., & Lewis, J. 2003. A Neural Network Bid/No Bid Model: The Case For Contractors In Syria. *Construction Management and Economics*, **21**(7), 737-744.