Examining sensitivity of financial performance at construction projects prequalification stage

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ABSTRACT

Construction projects are complicated in nature and require many considerations in contractor selection. One of the complicated interactions is that between performance with the project size, and contractor financial status, and size of projects contracted. At the prequalification stage, the financial requirements restrict the contractors to meet minimum limits in financial criteria such as net worth, working capital and annual turnover, etc. In construction projects, however, there are cases when contractors meet these requirements but show low performance in practice. The model used in the study predicts the performance by training of a neural network. The data used in the study are 72 of the most recent roadwork projects in Bahrain. The results are shown in terms of the sensitivity of changing one variable on the performance of all the 72 projects. These results can reflect on the methods currently used on contractors’ assessments in the tendering stage and support decision-makers in assessing contractors and selecting the best bidders.

Keywords: sensitivity analysis, financial performance, contractor selection, tendering, multi-layer perceptron.

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1. INTRODUCTION

Bidding involves analysing large and complex data (Cheng, Wang and Sun, 2012) to select the optimum bidder (Taylor et al., 2015). It needs setting criteria, and policies (Cheng, Wang and Sun, 2012) to shortlist the bidders to only those legally, technically and financially capable (Bushait and AI-Gobali, 1996) (Cheng, Wang and Sun, 2012). The main attributes of selecting the best contractor are the bid price, the financial status, the years of experience and former performance (Safa et al., 2017). In design-build contracts, three dimensions taken for assessment: the design and technique, finance, and management (Zhang et al., 2019). In general, the reputation and time and the most influential in selection as well as the material supply and completion with less financial problems (El-khalek, Aziz and Morgan, 2018). Roberts and Dowling found that better reputation firms stand greater profit and better financial performance (Roberts and Dowling, 2002). Thus, past failures, financial status, financial stability, credit ratings (Huang et al., 2014), are of the dominant assessment criteria (Hatush et al., 1997) (Marzouk, El Kherbawy and Khalifa, 2013).

The lowest bid is the widely held selection method (Cheng, Wang and Sun, 2012), the improvement in bidding exists in the prequalification process. Beside to that the prequalification causes cost that approximately forms the fifth of the local industry annual turnover (Rahman, 2014).

The financial criteria are leading dilemma worldwide as the ranking contractors stands on experience and financial stability (Bushait and Al-Gobali, 1996) (Arditi and Gutierrez, 1991). The general election approaches are either of three approaches (Nassar and Hosny, 2013): The first is short-listing bidders through a prequalification process by technical and financial evaluation to award then to the lowest bid. The second approach in the classification base on the proportion of bid offer to the technical score, then the contractors with the lower ratios are more preferred. Third, assigning contractors to groups and projects based on the project’s difficulty, type and size. In this research considers the third method which classifies contractors based on financial criteria to meet the project grade requirement. The groups classify contractors by financial criteria corresponding to project grades to avoid liquidity problems that cause a lack of performance and affect completion (Lee et al., 2018). In the extreme scenarios of these problems, the project enduring financial situations is more prone to change orders (Khanzadi, Nasirzadeh and Dashti, 2018), potential claims and incurring further costs.

Generally, there are several methods used in the evaluation are the average price, evaluating construction quality method and scoring system. The scoring system is used to recommended qualified bidders according to their overall score (Cheng, Wang and Sun, 2012). One of its limitations is the challenge to investigate the capabilities against the inexact or vagueness qualitative criteria (Li, Nie and Chen, 2007). Also that the prequalification is non-design research (Tah, Carr and Howes, 1999) yet it requires counting for uncertainties and risk assessment when setting the criteria thresholds (Afshar et al., 2017). The counting for that requires finding the interrelation between contractor characteristics and the performance in the field cannot be easily predicted using models not to mention the scoring methods.
Generally, capabilities are enhanced by partnering with participant (Wang et al., 2014) then prequalification affect their practices (Nazari et al., 2017) and has a proven relationship with project success (Al-Ageili and Alzobaei, 2016; Erzajj and Aljanabei, 2016; Acheamfour et al., 2019). Particularly, the financial capabilities is indicated as of the most important factor of contractors success following management and strategy factors (Kuwaiti, Ajmal and Hussain, 2018). Conversely, the larger companies doesn't show difference in marketing then smaller ones (Arditi, Polat and Makinde, 2008) although they differ in sales (Chan and Au, 2009). In the light of that, the Project Client "Roads Projects and Maintenance Department" RPMD in Bahrain counters difficult decision-making situations. In the first place, despite that the larger companies win contract after exceeding the lowest limits of financial criteria, they show low FP. Likewise, the nature of road works add more challenge that requires linking contractor with their meeting with the performance indicators (Partnerships, 2003). That is to say, contractors working in number of projects with their full workload capacity, and resources fully in use, premium payment needed for any extra work (Fayek, 1998). Otherwise, contractors suffer resources shortage that leads to decreasing effect on schedules owing to this complication (Nguyen et al., 2018) (Liu et al., 2018).

This study is not only beneficial for the client decision making but also to the dynamic relationship between the parties in road works projects (Emre and Hastak, 2009). By the same taken, it is good for organizations to consider it in the procurement decision (Chao and Hsiao, 2012) such as bid/no bid (Biruk, Jaśkowski and Czarnigowska, 2013) and mark-up value (Polat, Baytekin and Eray, 2015) in which financial status plays a main role. As a result, companies avoid business failures and (Cheng and Hoang, 2015) bankruptcy and ultimately find its effect on cost estimation and saving (Rafiei et al., 2018). Especially, for contractors, the financial capabilities are of their most important success factor after management and strategy factors (Kuwaiti, Ajmal and Hussain, 2018). The best modelling for this kind of complicated problems is Artificial Neural Networks that can process a larger amount of data and is used to predict the FP. The data includes a list of financially criteria ratios related to the contractor's bankruptcy potential to allow for a high degree of correlation with each other (Altman, 1968) and with the client Financial-Objectives – FP.

1. THE PERFORMANCE RELATED TO FINANCIAL CAPABILITIES FP

The data are from assessment reports prepared in RPMD in the Ministry of Works, Municipality Affairs and Urban Planning, in Bahrain. These reports contain evident data about the contractors that confirm they are capable of contracting legally, technically, and financially such as Certificates and Audited Bank Statement, etc. For when the lowest bid wins the contract, it is ascertained to a qualified bidder at the prequalification phase unless other less popular methods used (Ioannou, Asce and Awwad, 2010) methods used such as second lowest, average or below average (Ahmed et al., 2016).

During the execution of the construction projects, the client representatives check on the performance indicators of contractors in the construction site and keep count for assessment of the FP. The FP assessment is the level of achieving client financial obligations (Huang et al., 2013) which covers the following three main areas:

- Financial Capacity to pay all expenses such as material, labor, etc.
- Availability and appropriateness of the construction equipment, work machinery and tools.
- Adequacy in the supply of approved materials (materials as per specifications)

The client representative assesses the contractor performance in a number of varying sizes of Term Contracts -individual small works- to supervise practices during procurement and
works (Alan., 2011). Then, the average FP corresponds to performance along a cumulative number of Term Contracts TC. However, there are instances when contractors demonstrate higher and lower FP than average referred to as optimistic and pessimistic FP, respectively.

2. RESEARCH METHOD
The aim of the research is to find the correlation between the 24 variables and the value of the FP using the ANN, then find the sensitivity of the FP with change in each of the 24 variables.

2.1 Sensitivity analysis calculation
After applying the FP network to find the contractor average FP score, each one variable changes at a time to examine the FP score.

$$S_{p,xi} = \text{Sensitivity after changing characteristic } x_{i,org} \text{ to } x_{i}^{p}$$

where $p$ is the percentage of change in $x_{i,org}$ and $i$ is the variable number

The sensitivity due to change a contractor characteristic from original to maximum value:

$$S_{p,i} = \frac{PFC_{Av}(x_{i}^{p}) - PFC_{Av}(x_{i,org})}{PFC_{Av}(x_{i,org})}$$

(1)

3. ARTIFICIAL NEURAL NETWORK –ANN

One advantage of machine learning is their ability to be model-free (Reuter, Sultan and Reischl, 2018) and provide a simplified prediction that reduces the analysis time (Wee, Wong and Kyun, 2018). There are several kinds of research that proved the ability of ANN to solve complicated problems (Sivanandam and Paulraj, 2003; Cheng, Wang and Sun, 2012; Chou et al., 2015; Gandomi and Roke, 2015; Hung-wei and Ching-hung, 2017; Morfidis and Kostinakis, 2017; Mundher et al., 2017; Xu et al., 2017; Reuter, Sultan and Reischl, 2018; Wee, Wong and Kyun, 2018; Zhou et al., 2019). The implication of prequalification decision-making process by (Russell and Skibniewski, 1988) to the ANN is in Fig. 1:

The ANN models are used to solve challenging problems by processing independent variables resembling the neurons receiving stimuli in the human neural system. Therefore, ANN results can make more precise and reliable compared with other traditional, existing approaches (El-gohary et al., 2017). The ANN is used in prediction and proved superiority in solving engineering, and construction management and problems (Modin, 1995; Boussabaine, 1996; Hua, 1996; Li and Love, 1997; Shi, 1999; Emsley et al., 2002; Tam and Tong, 2003; Wanous, Boussabaine and Lewis, 2003; Al-Sobiee, Arditi and Polat, 2005; Ok and Sinha, 2006; Chao, 2010; Jha and Chockalingam, 2011; Goh and Chua, 2013; Odeyinka, Lowe and Kaka, 2013; Tordeux et al., 2019).

In the simplest form, the ANN consists of three layers, namely, input layers and an output layer and a hidden layer that is simply process inputs. While in ANN, the number of layers is higher than three to enable it to solve more complicated problems and possess a superiority to other types of prediction approaches (Efe, 2010).

3.1 Artificial Neural Network (ANN)
The multilayer perceptron (ANN) of this research consists of one hidden layer with 7 computation neurons to randomly train 70% of data, validate 15% and test 15% of the 72 Term Contract road works projects. Each term contract data is made of 24 variables consists of the accumulative amount and contractor characteristics as the inputs to the network. In the other hand, the FP values of term contracts are the target of this network training. considered as the variables in the study and they include the financial criteria that form a part in the financial
prequalification process. The prequalification models match the objectives of the owner based on engineering analysis (Gandomi and Roke, 2015) with the main criteria for contractor evaluation (Plebankiewicz, 2012). The illustration in Fig. 2 show the nonlinear transfer function used, specifically, “transig” (Lam, Lam and Wang, 2010). The activation of a neuron in the input layer, the one hidden layer, and the output layer are as follows:

\[
\text{net}_{jl} = \sum_{i=1}^{r(l-1)} \omega_{ijl} x_{ijl} + b_{jl} \quad j = 1, \ldots, t_l \text{ and } l = 2, \ldots, 8
\]  

(2)

Where \( \text{net}_{jl} \) is the activation of the \( j \)th neuron in \( i \)th layer, \( \omega_{ijl} \) is the weigh that links \( i \)th output of neuron in the former layer, i.e. \( x_{ijl} \), with the \( j \)th neuron in \( i \)th layer, \( t_k \) is number of neuron at \( i \)th layer, and \( x_{ijl} \).

An activated value of \( \text{net} \) converts the net input into an output using a transfer function so the output of this layer's neuron becomes an input to the next layer's neurons using the Hyperbolic Tangent Transfer Function:

\[
f(\text{net}_{jk}) = \frac{2}{1 + e^{-2\text{net}_{jk}}} - 1
\]  

(3)

4. RESULTS AND DISCUSSION

The performance of the network is measured using the Mean Square Error MSE which expressively dropped with the ANN training performance as shown in Fig. 2. Besides, the error histogram demonstrating the values and occurrence of difference between predicted FP – network output- and targets. The values of maximum error are reasonable for this kind of estimation as shown in Fig. 3. The regression values of the trained validated and tested records are shown in Fig. 4. The application of this trained model requires entering the inputs to predict the FP (Kadhim and Erzaij, 2020). Especially that the successful methods require a combination of antiquity and ease of application (Jato-espino et al., 2014). Finally, the progress of training performance with epochs is displayed in Fig. 5.

4.1 Sensitivity of Average FP

Since the relationship between the input and output is complicated and each contract has it uniqueness, the sensitivity analysis links the change in variables with predicted change in FP in all term contracts in the study. The change in one variable befall in 11 change groups from -240 to 360% associated with the predicted FP sensitivity. The graph of the mean FP sensitivity shows the nature of whole change demeanor. By and large, the change in variables link with FP sensitivity is either evident, such that the FP is proportional or inversely related with the change in variables, or not evident of sensitivity trends. The sensitivity values in this example are varying in the relationship with characteristics values increasing or decreasing into the following arrangements:

In the first place, the FP sensitivity mean curves in Fig. 6 increase slightly with the variable increase and decreases significantly with the decrease in variables values. Chiefly, this directly proportional relationship fits for competitive contractors’ characteristics result in improving FP. Namely, the curve of aggregate completed projects, the largest completed project and the aggregate ongoing projects. In like manner, the FP improves when accumulated amount of assessed project is larger as shown in Fig. 7. The curves in this figure increase with the variable increase nonetheless it marginally increases with the variable’s values reduction. The FP shown in Fig. 7 significantly increase with the increase in variables values. Namely, the equity net-worth, paid-up capital and the amount paid to contractor at point of assessment. The third set of sensitivity curves in Fig. 8 are of the opposite to the previous figures That is to say, the
contractors who have higher Net-worth, Average per Work, and Working capital may financially perform worse.

5. CONCLUSIONS AND RECOMMENDATIONS

Although it appears rational to anticipate that more competing contractors who meet the prequalification financial criteria perform better than less competitive ones, the outcome of this study demonstrates that this is not certainly right. This is because study reveals that the current scoring system in the prequalification phase is not sufficient in screening contractors in complicated situations such as when contracting in several projects at a small net-worth. To enumerate, increasing some characteristics values that suggest to score contractors higher in traditional prequalification system can associate with drop in the actual FP value. Specifically, the net-worth, average amount per work and working capital.

Although each project has its own uniqueness in characteristics interactions but taking the mean sensitivity of FP in consideration, can help understand the general prequalification situation much better. Markedly, hiring contractors with higher equity, paid-up capital, and network may be associates with the FP dropping.

The use of the model in predicting FP and analyzing the sensitivity is useful for decision makers and contractors in the prequalification phase to predict each bidder FP.

Understanding of contractor financial capabilities and predicts the contractor performance in the early stages.
Anticipating risks of low performance related to financial capabilities is important for planning and performing risk assessments.
Early Knowledge of the predicted value of FP help decision makers put contractual restrictions on criteria such as the number of projects the contractors are allowed to be involved in while executing the construction project.

For these reasons, the use of this model is not only for clients benefits it is also for the contractors’ survival in the industry by detecting their potential financial failure at early stages by avoiding or reducing it. To emphasize, avoiding prequalifying contractors whose strategy is to win numerous contracts at a time by offering bids with low mark-up values and risking the FP.

For the most part, the use of 72 term contracts in ANN network trained model satisfactorily (1) correlates the contractors’ historical data to predict the FP values, (2) answer its "what if?" questions in the prequalification phase, (3) explaining the current contractor’s behaviors.

Although this may be true, using this model, the FP behavior potentially revolve as the system grows smarter than department shall originate continuous improvement scheme to reduce predicting FP uncertainty. Correspondingly, MoW may ask for more detailed data such as (a) resources allocation the manpower and equipment throughout the ongoing projects as well as a (b) shorter period financial statement and records instead of using the annual statement in representing contractor capabilities.

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Figure 1. Architecture of one-layer feed-forward neural network with Levenberg-Marquardt backpropagation algorithm.

Figure 2. Performance of ANN model.
Figure 3. Error Histogram of the data trained, validated and tested for Average FP.

Figure 4. The correlation regression.
Figure 5. The training and validation performance with epochs.

Figure 6. Mean FP slightly decreasing with the decrease in in variables.
Figure 7. Mean FP values increase with increase in variables.

Figure 8. Mean FP decreasing with increase of in variables.

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