Prediction of the Performance Related to Financial Capabilities Using Multilayer Perceptron

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Abstract. In construction projects, there are circumstances when contractors meet financial prequalification requirements but show low financial performance in practice. These cases bring about the complexity in contractor selection. Hence, the aim of this research is to build a prediction model that finds contractors’ financial performance to support decision makers assess contractors more efficiently in prequalification phase. Thus, this study takes recent roadwork Term Contracts Projects with each with the corresponding contractor's records to train the model to predict Performance related to Financial Capabilities PFC. The Multilayer Perceptron MLP is utilized to find the nonlinear correlation between the PFC and contractors' characteristics. The research finds that more financial competitive contractors show less financial performance than less competitive ones. The findings of the research help the client improve the current contractors’ evaluation system to exhaust the possibilities of financial performance.

Keywords: Artificial neural network, financial ratios, pre-qualification, contractor performance, contractor selection.

1. Introduction

Bidding involves multi-criteria decision-making under uncertainty and analysing large and complex data [1] to select a contractor or supplier [2]. It requires setting criteria, and policies [1] to shortlists the bidders to only those legally, technically and financially capable [3]. With this in mind, bids are evaluated through the price, quality evaluating and scoring system. The scoring system is used to recommended qualified bidders according by their overall score [1]. Otherwise, widely held method of lowest price is used [1], the improvement in contractor selection can enhance throughout the prequalification process. Another key point, upgrading the prequalification system contributes to cost efficiency that may reach up to the fifth of the local industry annual turnover as in Scotland [4]. Moreover, prequalification affect practices [5] and has a demonstrated relationship with project success [6] and risk management [7]. On the other hand, the prequalification is non-design investigation [8] that requires counting for uncertainties and risk assessment when setting the criteria thresholds [9]. Besides, one of its limitations is the challenge to investigate the capabilities against the inexact or vagueus qualitative criteria [10].
One of the key selection factors is the financial capabilities, which is deliberated as the most important factor of contractors success following management and strategy factors [11]. On the contrary, the larger companies do not show difference in marketing then smaller ones [12] despite that they differ in sales [13]. In the light of that, the Project Client counters difficult decision-making situations. Despite that the larger companies win contract after exceeding the lowest limits of financial criteria, they show low PFC. Likewise, the nature of road works add more challenge that requires linking contractor with their meeting with the performance indicators [14] (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 [15] (Fayek, 1998). Otherwise, contractors suffer resources shortage that affects schedules [16] [17] and operations that in turn impacts the performance [18].

This study aims to develop client decision making model that adds to the dynamic relationship between the parties in road works projects [19] (Emre and Hastak, 2009) that results in improving cost and schedule outcomes [20]. Likewise, it is important for other parties to consider this nature of correlation in the procurement decision [21] (Chao and Hsiao, 2012) such as bid/no bid [22] and mark-up value [23] in which financial status plays a main role. As a result, companies avoid business failures and [24] bankruptcy and ultimately find its effect on cost estimation and saving [25]. Especially, for contractors, the financial capabilities are of their paramount success factor after management and strategy factors [11]. Generally speaking, the successful methods require a combination of antiquity and ease of application [26]. Therefore, the modelling used in this analysis is by Multilayer Perceptron MLP which is a mode of Artificial Neural Networks that predict the PFC using actual data set and assessments of earlier term contracts. 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 [27] and with the client financial objectives as the “performance targets” [28]. Explicitly, the expectations and objectives influence the prequalification process [29] Additionally, the sensitivity

2. Literature Review

2.1 Contractor Selection Approaches

As a matter of fact, the contractor election approaches are either of three approaches [30]: 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 projects 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 [31]. In the extreme scenarios of these problems, the project enduring financial situations is more prone to change orders [32], potential claims and incurring further costs.

2.2 Selection Criteria

The main attributes of selecting the best contractor are the Bid Price, the Financial Status, the Years of Experience and Former Performance [33]. The research in design-build type of contract found that the three dimensions taken in contractors' assessment prequalification which are design and technique, finance, and management [34]. Furthermore, the reputation and time are considered the most influential in selection while the most important factors are the material supply and completion with less financial problems [35]. Especially that Roberts and Dowling [37] found that better reputation firms stand greater profit and better financial performance [36]. The past failures, financial status, financial stability, credit ratings [37], are of the dominant contractor selection criteria [38] and subcontractors [39]. Authentically, clients and contractors come to an understanding on selection criteria and that the bid price is leading followed by experience and reputation [40]. All in all, aims to support award to be based on knowledge and capabilities to assure awarding to the financially and technically capable contractors [1].
2.3 Prequalification Financial Criteria
The classification of contractors at prequalification is done based on financial capitals, experience, and workforce and equipment [3]. The exploration of financial capabilities involves analysing financial statement ratios and financial references credits [41]. Accordingly, the liquidity and profitability of a contractor requires analysing ratios and trends along with the contractor's historical and industry since the interpretation of these ratios is requires accumulated experience and interrelation understanding [42]. Henceforth, the criteria can include the staff and equipment, financial capacity, former performance, administrative experience and management systems [43].

3. Research Method
The aim of the research is attained by finding the correlation between the 24 variables from term contract collected data sets with the value of the assessed PFC using the MLP. At that point, sensitivity analysis is performed to find the influence of change one variable over the average PFC.

3.1 Data Collection
A team was established to prepare the term project assessment reports which contains 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 [44] methods used such as second lowest, average or below average [45].

3.2 Data Source
In the prequalification phase the bidders are enforced to submit concrete evidence to prove compliance with the requirement of the project for testing compliance with financial criteria in two stages. The aim of these requirements is to meet the contracting sequence and schedule, increase competition to track down lower prices, procure the quality project, foster the evolution of indigenous contractors [46].

The First Stage
This stage allows assigning points only when contractor passes the lowest limits financial criteria values shown in Table 1. The total score of adding the points shall exceed or not be less than 75 points to pass this stage. The points assigned are based on pass or fail so only when contractor passes lowest limit values in Working Capital and Net worth earns 30 points for each while 20 for each of Current Ratio and Quick Acid Test Ratio.

The Second Stage
After passing the first stage, the Audited Financial Statement further to assess the criteria that are related to financial ratios that could lead to financial problems. They are related but not limited to the liquidity, profitability, operational efficiency, leverage. In more detail, the financial problems and solutions are usually attributed to the sales, inventories current assets, and debt [31]. Specifically, when a firms pass through a crisis, there is an uncertain policy to which they would go along with, to be exact, whether to address liquidity problems at the expense of profitability or vice versa [47] [48].

Liquidity: The liquidity measures the ability to meet short- and long-term obligations using the quick ratio and the current ratio [49]. For instance, Huang et al. [50] found that the majority of contractors' failure is because of the lack of liquidity rather than the insufficiency of resources and management skills [50]. Since the financial health of a contractor is the key to success in a construction project, the owner obligation is to be well-informed about it from bidding until projects completion. For that reason, financial feasibility advantages clients save public funds [51]. Particularly, it is recommended to initialize a feasibility study by assessing liquidity and planning to avoid issues as well as monitoring the liquidity status during execution [31].

Liquidity study in the reports includes Current Ratio, Quick Ratio, and Working Capital.

Profitability Sustainability: profitability and liquidity form the key to the financial distress configuration [47]. Likewise, the instability of profit forms risks, even if profitability is high [52]. It includes:
(1) The Gross Profit Margin (GPM): it measures the contractor profit margin to the indirect costs. Then, higher values mean the contractor can cover the cost of their purchases by selling with higher values [47].

(2) Net Profit Margin is the contractor ability to cover the working and operating costs. The higher the ratio, the more efficient the covering of the operating expenses by the level of sales [47].

(3) The Return on Assets (ROA): it defines the performance of the total asset and evaluates the capital structure at a leverage status [47].

(4) The Return on Equity (ROE): it defines the performance of the owner’s capital considering owner capital expresses [47]. Ideally, in an efficient market, firms' equity reveals the quantitative and qualitative information about their survivability [53].

Operational Efficiency considers more specific a measure such as the number of the day during which turnover occurs.

(1) Accounts Receivable Turnover: This is the number of times through the year at which receivables are turned over. It indicates the effectiveness of the firm in using receivables in collecting debt on extended credit.

(2) Inventory Turnover, which is related to the speed of selling to minimizing storing and performance of inventory management [47].

(3) Total Asset Turnover measures how well the contractor is efficient in the business by generating sales per assets.

Leverage: it demonstrates the contractor utilization of the debt and its risk of liquidity crunch when profitability declines. Typically, when the long-term debts to total assets ratio increase the debt becomes riskier [54] and costlier, demonstrating difficulty in producing adequate cash flow. For this purpose, the following measurements are critical financial criteria:

(1) Debt to Equity Ratio: the combination of debt and equity form the essence of the financial structure [55] and a vital measurement in financial evaluation.

(2) Gearing Ratio specifies the magnitude leverage the company has in terms of borrowed funds against equity.

3.3 PFC Assessment

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 PFC. The PFC assessment is the level of achieving client financial obligations [50] which covers the following three main areas:

- Financial Capacity to pay all expenses such as material, labour, 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 [56]. Then, the average PFC corresponds to performance along a cumulative number of Term Contracts TC. However, there are instances when contractors demonstrate higher and lower PFC than average referred to as optimistic and pessimistic PFC, respectively.

3.4 PFC data

During a period of time, contractors deliver unalike PFC scores illustrate as the average, optimistic, and pessimistic and their values shown in Figure 1:
The Average of Actual PFCs of on-going Term Contracts:
\[ PFC_{AV} = \frac{\sum_{TC} PFC_{TC}}{TC} \]  

(1)

The optimistic PFC of on-going Term Contracts
\[ PFC_{opt} = \max_{TC} PFC_{TC} \]  

(2)

The pessimistic PFC of on-going Term Contracts
\[ PFC_{pes} = \min_{TC} PFC_{TC} \]  

(3)

The Average of Actual PFC when all Term Contracts are assessed:
\[ PFC_{AV} = \frac{\sum_{N} PFC}{N} \]  

(4)

The optimistic PFC of all Term Contracts completed by a contractor:
\[ PFC_{opt} = \max_{N} PFC_{N} \]  

(5)

The pessimistic PFC of all Term Contracts completed by a contractor:
\[ PFC_{pes} = \min_{N} PFC_{N} \]  

(6)

\[ PFC = \text{Performance Related to Financial Capabilities} \]
\[ TC = \text{Number of Term contracts evaluated} \]
\[ N = \text{Total number of term contracts evaluated} \]
\[ TCA = \text{Term Contract Amounts} \]

4. Artificial Neural Network Application
One advantage of machine learning is their ability to be model-free [57] and provide a simplified prediction that reduces the analysis time [58]. There are several kinds of research that proved the ability of ANN to solve complicated problems [59]; [1]; [60]; [61]; [62]; [63]; [64]; [65]; [57]; [58]; [66]. The implication of prequalification decision-making process by [67] to the ANN is in Figure 2:
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 [68]. The ANN is used in prediction and proved superiority in solving engineering, and construction management and problems [69]; [70]; [71]; [72]; [73]; [74]; [75]; [76]; [77]; [78]; [79]; [80]; [81]; [82]; [83].

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 MLP, 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 [84].

4.1 Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) of this research consists of 6 hidden layers each with 32 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

**Figure 2.** FP model building flowchart
accumulative amount and contractor characteristics as the inputs to the network. In the other hand, the PFC values of term contracts are the target of this network training. This is done for the prequalification model to match the objectives of the owner based on engineering analysis [61] and the criteria for contractor evaluation [85]. The illustration in Figure 3 show the nonlinear transfer function used, specifically, “transig” [86].

Figure 3. Architecture of six-layer feed-forward neural network with Conjugate Gradient Back-propagation with Fletcher-Reeves Restarts learning algorithm

The activation of a neuron in the input layer, the six hidden layers, and the output layer are as follows:

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

(7)

Where net_{jl} is the activation of the \( j^{th} \) neuron in \( l^{th} \) 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 \( l^{th} \) layer, \( t_l \) is number of neuron at \( l^{th} \) layer, and \( x_{ijl} \).

An activated value of 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:

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

(8)

4.2 Conjugate Gradient Back-propagation with Fletcher-Reeves Restarts.

The algorithm that train the MLP in all layers is the Conjugate Gradient Back-propagation with Fletcher-Reeves Restarts introduced by [87] and shown in Figure 3. It can train the networks that has weights, biases and inputs with derivative of quadratic function.

To Solve problem $AX=B$:
\[ F(X) = \| AX - B \|^2 \] (9)

\[ d_X F = 2 A^T (AX - B) \] (10)

Where the lowest value of \( F(X) \) occurs when gradient \( g=0 \)

\[ X_1 = X_0 + \alpha_0 \Delta X_0 \] (11)

Calculation of steepest direction in first Iteration:

\[ S_0 = \Delta X_0 \] (12)

Iterations are made along Conjugate Directions \( S_k \) are and stop when no improvement is made when steepest descent direction reached and direction resets:

\[ \Delta X_{k+1} = -d_X F(X_{k+1}) \] (13)

\[ \beta_{k+1} = \frac{\Delta X_{k+1}^T \Delta X_{k+1}}{\Delta X_k^T \Delta X_k} \] (14)

\[ S_{k+1} = \Delta X_{k+1} + \beta_{k+1} S_k \] (15)

\[ X_{k+1} = X_k + \alpha_k \Delta X_k \] (16)

\[ \alpha_k = \arg \min_{\alpha} F(X_{k+1} + \alpha_{k+1} S_{k+1}) \] (17)

\[ X_{k+1} = X_k + \alpha_k S_k \] (18)

4.3 Sensitivity analysis calculation

After applying the PFC network to find the contractor average PFC score, each one variable changes at a time to examine the PFC 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:

\[ S_{p,i} = \frac{PFC_{Av}(x_i^p) - PFC_{Av}(x_{i,org})}{PFC_{Av}(x_{i,org})} \] (19)
5. Results

The performance of the network is measured using the Mean Square Error (MSE) which expressively dropped with the MLP training as shown in Figure 4.

![Figure 4. Performance of MLP model](image)

Besides, the error histogram demonstrating the values and occurrence of difference between predicted PFC – network output- and targets. The values of maximum error are reasonable for this kind of estimation as shown in Figure 5.

![Figure 5. Error Histogram of the data trained, validated and tested for Average FP](image)

Equally important, the regression of this correlation approaches to 1 in the trained, verified, and tested data as well as reasonable error boundaries as shown in Figure 6.

![Figure 6. Error Boundaries](image)
Figure 6. regression of the PFC model for trained, tested and validated samples

The regression values and training states are also shown in Table 2 to compare the strength of correlation between inputs and outputs using a different perspective. In one hand, the results show that the use of one output to find either the optimistic, pessimistic of average individually is better than finding them all in one network. A single output network predicts only one of them while the three-output network predicts all of the three outputs values. The prediction used in this study is the single average PFC since its relatable to the current reporting system and because it showed least MSE and highest regression value.

5.1 Sensitivity of Average PFC
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 PFC in all term contracts in the study. The change in one variable befall in change groups ranging from -240 to 360% associated with the predicted PFC sensitivity. The graph of the mean PFC sensitivity shows the nature of whole change demeanour. By and large, the change in variables link with PFC sensitivity is either evident, such that the PFC is proportional or inversely related with the change in variables, or not evident of sensitivity trends. The sensitivity values are taken for all term contracts in the study to observe the relationship of characteristics accept that they fall in 11 change groups values. The change of PFC with the alteration of variables values are illustrated in Figure 7 to Figure 11 and reflected in the following section.
6. Discussion

In the first place, the PFC sensitivity mean curves in Figure 8 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 PFC. Namely, the curve of amount of completed projects, the average collection period, return on equity, and return on asset. In like manner, the PFC improves when accumulated amount of assessed project is larger.

The second set of curves shown in Figure 9 decrease significantly with the variable increase nonetheless it marginally increases with the variable’s values reduction. The variables that logically fit into this relationship is the aggregate ongoing projects, and total liability per asset despite the fact that ongoing is not considered in scoring contractors as expressed in Table 3. Nevertheless, the other variables shown in Figure 9 designate competitiveness yet their increase cause decline in PFC value. The third set of sensitivity curves in Figure 10 are of the same nature of the previous figure except that the extreme decrease in these variables’ consequences in PFC drop. Forthwith, contractors with higher gross profit per asset, gross profit margin, and profit margin in former years do not necessarily perform better.
Figure 8. Mean PFC decreasing with increase of in variables

Figure 9. Mean PFC decreasing with increase in variables
Figure 10. Mean PFC value fluctuate as variables values change

The next PFC sensitivity curves presented in Figure 11 fluctuate when variables increase proofing that their increase do not necessarily improve the PFC. Conversely, when the variables values fall, the expected PFC value decrease. The last curves concave representing insensitive variables association with the PFC values as shown in Figure 12. To put it differently, the PFC values potentially drop with the increase or decrease of the variable’s values.

Figure 11. Mean PFC curve is concaved
7. 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. To enumerate, increasing some characteristics values that suggest to score contractors higher in traditional prequalification system can associate with drop in the actual PFC value. Although each project has its own uniqueness in characteristics interactions but taking the mean sensitivity of PFC in consideration, can help understand the general prequalification situation better. Markedly, increasing in the values of largest completed project in the past, paid-up capital, annual turnover, working capital per asset, and the number of equipment can associate the PFC dropping. Moreover, there are competitive characteristics that are not ascertained to be either associated with improving nor dropping in PFC values. In particular, net worth, annual average amount per work, manpower, equity net worth, working capital, current ratio, gearing ratio and debit/equity ratio. The use of the model in predicting PFC and analysing the sensitivity is useful for decision makers and contractors in the prequalification phase to predict each bidder PFC:

- 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.

Figure 12. continuous improvement system
Early Knowledge of the predicted value of PFC 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 emphasise, avoiding prequalifying contractors whose strategy is to win numerous contracts at a time by offering bids with low mark-up values and risking the PFC. For the most part, the use of 72 term contracts in MLP network trained model satisfactorily (1) correlates the contractors' historical data to predict the PFC values, (2) answer its "what if?" questions in the prequalification phase, (3) explaining the current contractor’s behaviours. Although this may be true, using this model, the PFC behaviour potentially revolve as the system grows smarter then department shall originate continuous improvement scheme to reduce predicting PFC uncertainty as shown in Figure 12. 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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