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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.

دراسة حساسية الأداء المالي في مرحلة التأهيل المسبق في مشاريع الإنشاء

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الخلاصة

مشاريع البناء معقدة بطبيعتها وتتطلب العديد من الاعتبارات عند اختيار المقاول. أحد التفاعلات المعقدة تلك التي بين الأداء مع حجم المشروع، والوضع المالي للمقاول، وحجم كل المشاريع المتعاقد عليها المقاول. في مرحلة التأهيل المسبق للمقاول، هنالك حد أدنى للمعايير المالية التي يجب أن توفى من قبل المقالوين مثل القيمة الصافية ورأس المال العامل والدوران السنوي، وما إلى ذلك. ورغم ذلك فإن هنالك حالات عندما يفي المقاولون بهذه المتطلبات ولكنه يقدم أداءا ضعيفا في الواقع. إن النموذج المستخدم في الدراسة يتنبأ بالأداء من خلال تدريب شبكة عصبونية. البيانات المستخدمة في الدراسة هي 72 من أحدث

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مشاريع أعمال الطرق في البحرين. يتم عرض النتائج من حيث حساسية تغيير متغير واحد على الأداء في كل المشاريع المستخدمة في الدراسة. تكمن أهمية هذه الدراسة في أنها يمكن أن تنعكس على الطرق المستخدمة حاليًا في تقييمات المقاولين في مرحلة المناقصة وأن تدعم صناع القرار في تقييم المقاولين واختيار أفضل مقدمي العروض.
الكلمات الرئيسية: تحليل الحساسية، الأداء المالي ، اختيار المقاول ، العطاءات ، شبكة عصبونية متعددة الطبقات.

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 shortlists 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: thedesign 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 AI-Gobali, 1996)(Arditi and Gutierrez, 1991)**. The general election approaches are either of three approaches**(Nassar and Hosny, 201**3): 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-Ageeli and Alzobaee, 2016; Erzaij 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.

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

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

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

$$S_{p,i} = \frac{PFC_{Av}(x_i^p) - PFC_{Av}(x_{i,org})}{PFC_{Av}(x_{i,org})} \quad (1)$$

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-Sobiei, 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:

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

Where net_{jl} is the activation of the j^{th} neuron in i^{th} layer, ω_{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, andx_{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*:

$$f(\text{net}_{jk}) = \frac{2}{1+e^{-2\text{net}_{jk}}} - 1 \qquad (3)$$

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 then 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.

6. ACKNOWLEDGMENT

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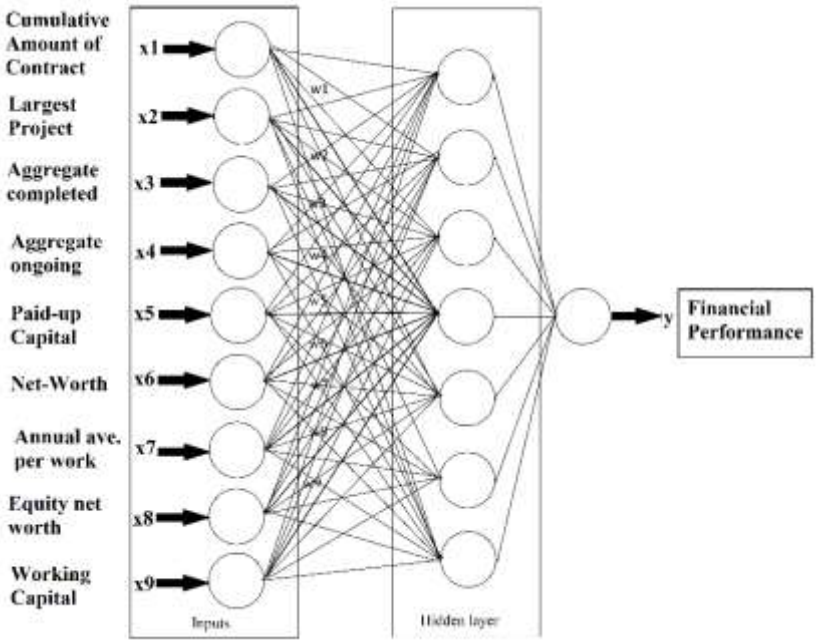

Figure 1. Architecture of one-layer feed-forward neural network with Levenberg-Marquardt backpropagation algorithm.

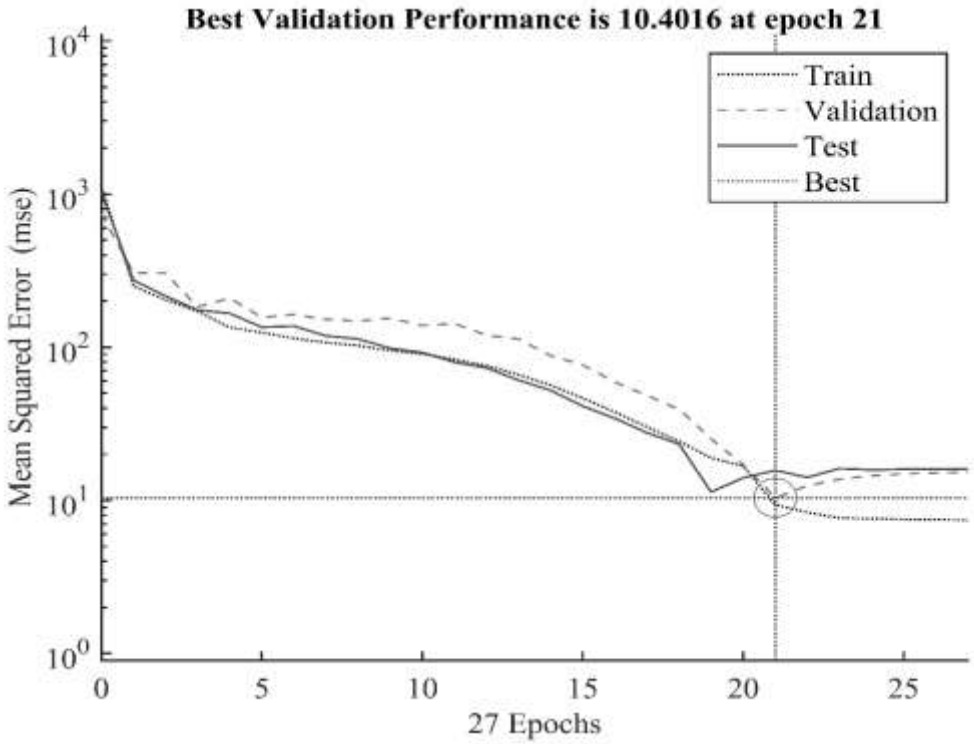

Figure 2. Perfomance of ANN model.

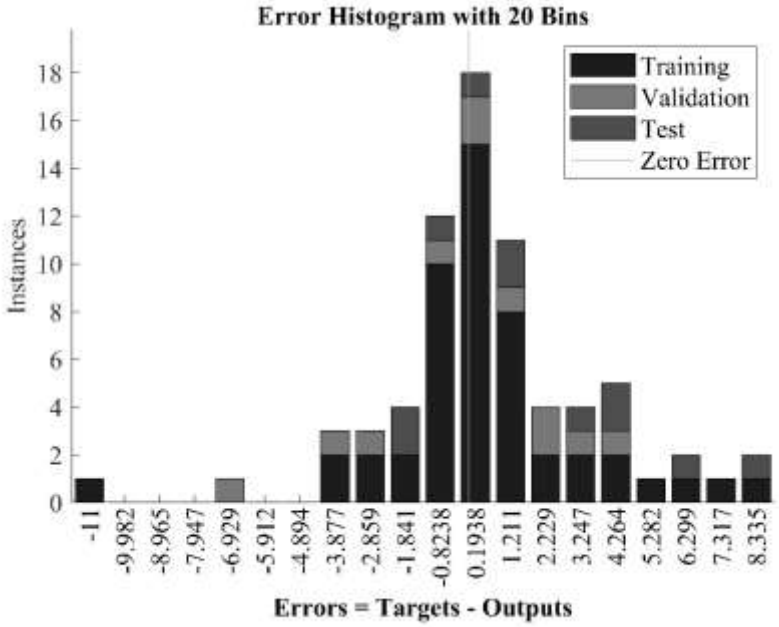

Figure 3. Error Histogram of the data trained, validated and tested for Average FP.

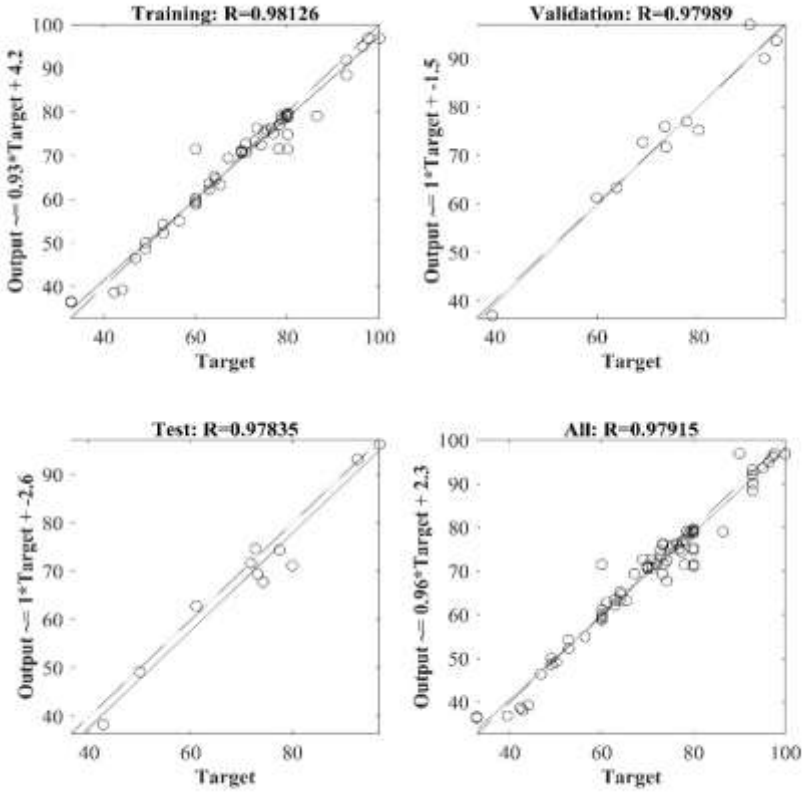

Figure 4. the correlation regression.

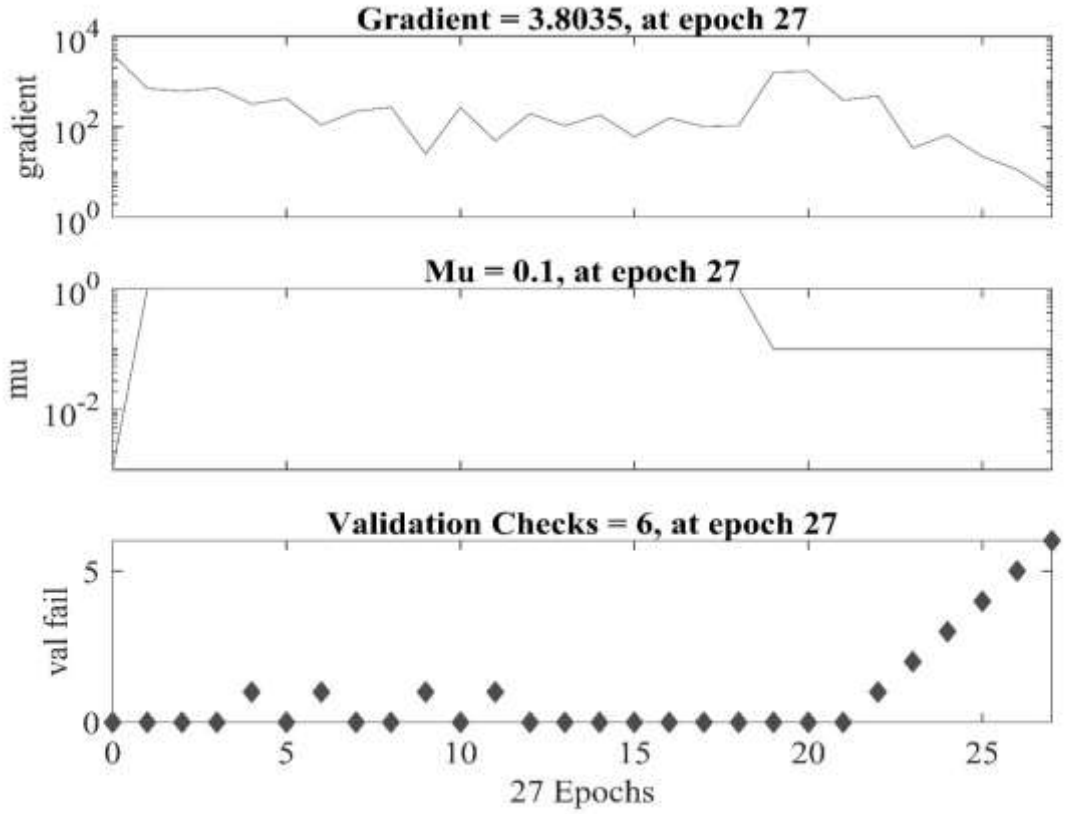

Figure 5. the training and validation performance with epochs.

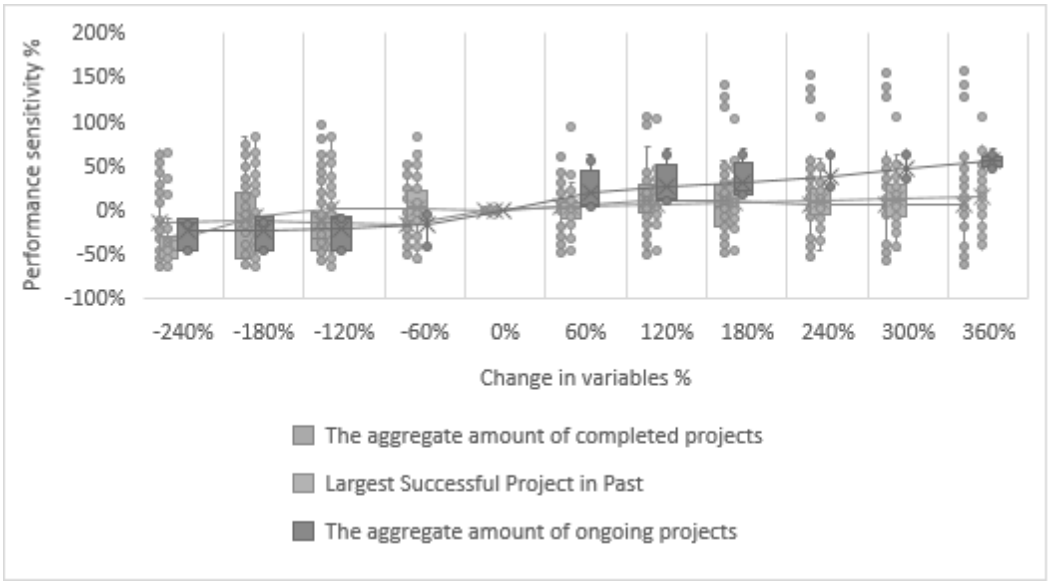

Figure 6. Mean FP slightly decreasing with the decrease in in variables.

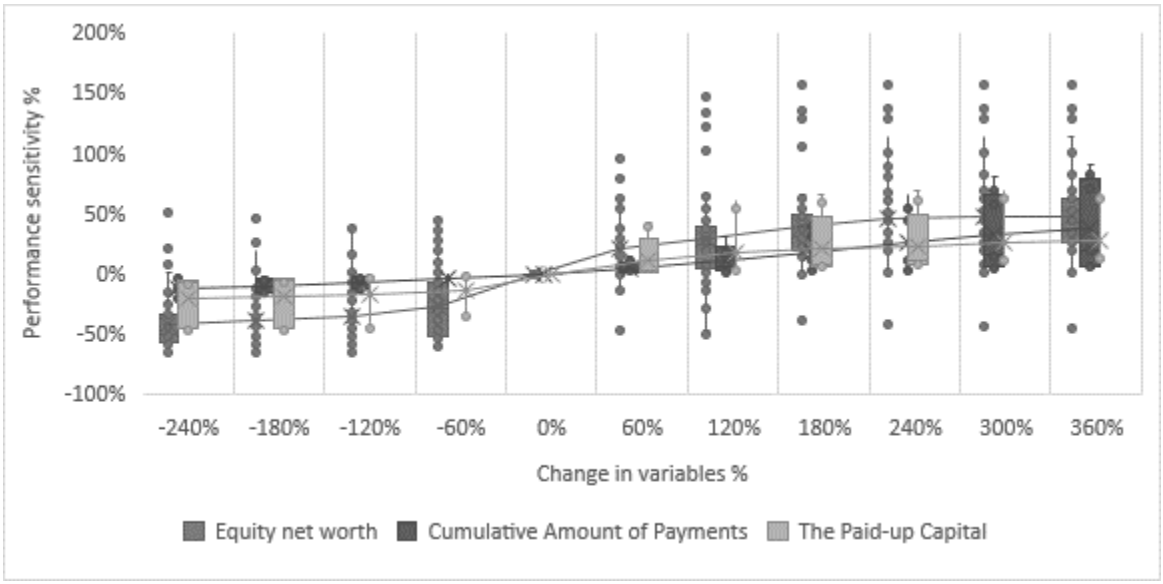

Figure 7. Mean FP values increase with increase in in variables.

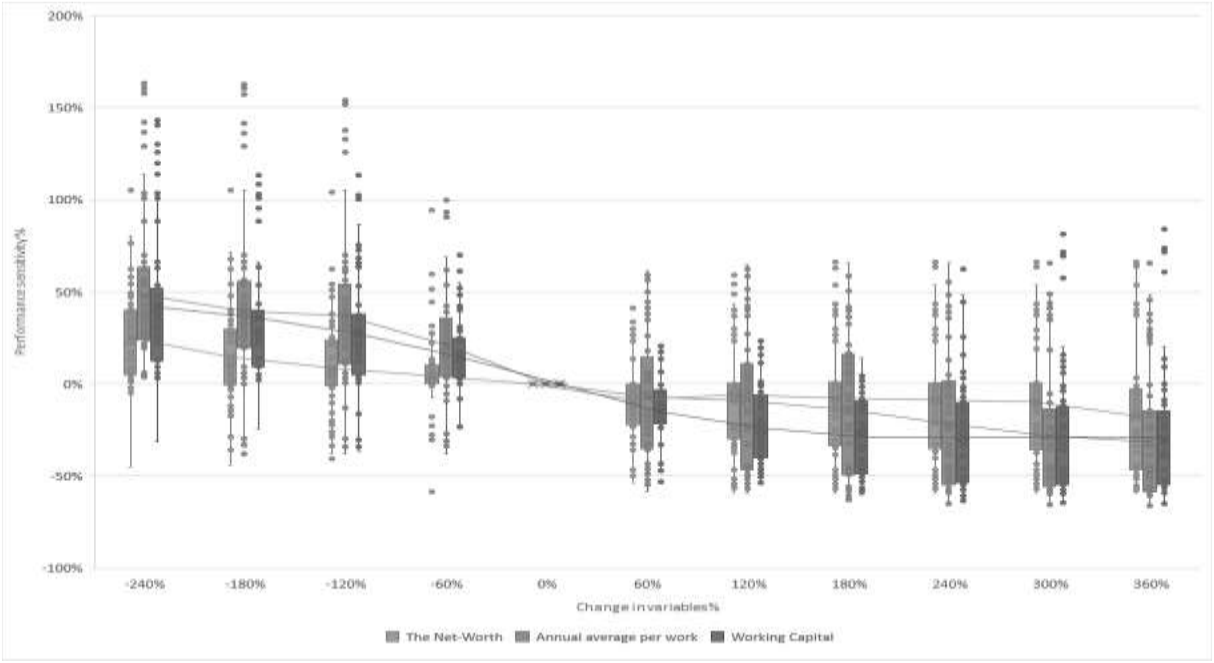

Figure 8. Mean FP decreasing with increase of in variables.

REFERNCES

- Acheamfour, V. K. *et al.* (2019) 'Ascertaining the impact of contractors pre-qualification criteria on project success criteria', *Engineering, Construction and Architectural Management*. doi: 10.1108/ECAM-03-2018-0110.
- Afshar, M. R. *et al.* (2017) 'A type-2 fuzzy set model for contractor prequali fi cation', *Automation in Construction*, 84(January 2016), pp. 356–366. doi:

10.1016/j.autcon.2017.10.003.

- Ahmed, M. O. *et al.* (2016) 'Construction Bidding and the Winner's Curse : Game Theory Approach', *Journal of Construction Engineering and Management*, 142(2), pp. 1–9. doi: 10.1061/(ASCE)CO.1943-7862.0001058.
- Al-Ageeli, H. K. and Alzobaee, A. S. J. A. (2016) 'Critical Success Factors in Construction Projects (Governmental Projects as a Case Study)', *Journal of Engineering*, 22(3).
- Al-Sobiei, O. S., Arditi, D. and Polat, G. (2005) 'Predicting the risk of contractor default in Saudi Arabia utilizing artificial neural network (ANN) and genetic algorithm (GA) techniques', *Construction Management and Economics*, 23(4), pp. 423–430. doi: 10.1080/01446190500041578.
- Alan., G. (2011) 'Delivering best value in the small works portfolio of public sector organizations when using preferred contractors', *Construction Management and Economics*, 29(9), pp. 891–900. doi: 10.1080/01446193.2011.617377.
- Altman, E. I. (1968) 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *The Journal ofFinance*, 23(4), pp. 589–609.
- Arditi, B. D. and Gutierrez, A. E. (1991) 'Factors affecting U.S. contractors' performance overseas', *Journal of Construction Engineering and Manageme*, 117(1), pp. 27–46.
- Arditi, D., Polat, G. and Makinde, S. A. (2008) 'Marketing Practices of U.S. Contractors', *Journal of Management in Engineering*, (October), pp. 255–264. doi: 10.1061/(ASCE)0742-597X(2008);4(255).
- Biruk, S., Jaśkowski, P. and Czarnigowska, A. (2013) 'Modelling contractor's bidding decision', *Engineering Management in Production and Services*, 9(1), pp. 64–73. doi: 10.1515/em.
- Boussabaine, A. H. (1996) 'The use of artificial neural networks in construction management: A review', *Construction Management and Economics*, 14(5), pp. 427–436. doi: 10.1080/014461996373296.
- Bushait, A. and AI-Gobali, K. (1996) 'Contractor prequalification in saudi arabia', *Journal of Management in Engineering*, 12(2), pp. 50–54.
- Chan, E. H. W. and Au, M. C. Y. (2009) 'Factors Influencing Building Contractors ' Pricing for Time-Related Risks in Tenders', *Journal of Construction Engineering and Management*, (March), pp. 135–145.
- Chao, L. C. (2010) 'Estimating project overheads rate in bidding: DSS approach using neural networks', *Construction Management and Economics*, 28(3), pp. 287–299. doi: 10.1080/01446190903473782.
- Chao, L. and Hsiao, C. (2012) 'Fuzzy model for predicting project performance based on procurement experiences', *Automation in Construction*. Elsevier B.V., 28, pp. 71–81. doi: 10.1016/j.autcon.2012.07.003.
- Cheng, M.-Y. and Hoang, N.-D. (2015) 'Evaluating Contractor Financial Status Using a Hybrid Fuzzy Instance Based Classifier: Case Study in the Construction Industry', *IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT*, 62(2), pp. 184–192. doi: 10.1109/TEM.2014.2384513.
- Cheng, T., Wang, Y. and Sun, Y. (2012) 'Development and application of tender evaluation decision-making and risk early warning system for water projects based on KDD', *Advances in Engineering Software*. Elsevier Ltd, 48(2012), pp. 58–69. doi:

10.1016/j.advengsoft.2012.02.003.

- Chou, J. S. *et al.* (2015) 'Optimized artificial intelligence models for predicting project award price', *Automation in Construction*. Elsevier B.V., 54, pp. 106–115. doi: 10.1016/j.autcon.2015.02.006.
- Efe, M. Ö. (2010) 'A comparison of networked approximators in parallel mode identification of a bioreactor', *Advances in Engineering Software*, 41, pp. 1132–1147. doi: 10.1016/j.advengsoft.2010.07.004.
- El-gohary, K. M. *et al.* (2017) 'Engineering Approach Using ANN to Improve and Predict Construction Labor Productivity under Different Influences', *Journal of Construction Engineering and Management*, 143(8), pp. 1–10. doi: 10.1061/(ASCE)CO.1943-7862.0001340.
- El-khalek, H. A., Aziz, R. F. and Morgan, E. S. (2018) 'Identification of construction subcontractor prequalification evaluation criteria and their impact on project success', *Alexandria Engineering Journal*. Faculty of Engineering, Alexandria University. doi: 10.1016/j.aej.2018.11.010.
- Emre, M. and Hastak, M. (2009) 'Automation in Construction A decision support system for selecting the optimal contracting strategy in highway work zone projects', *Automation in Construction*. Elsevier B.V., 18(6), pp. 834–843. doi: 10.1016/j.autcon.2009.03.007.
- Emsley, M. W. *et al.* (2002) 'Data modelling and the application of a neural network approach to the prediction of total construction costs', *Construction Management and Economics*, 20(6), pp. 465–472. doi: 10.1080/01446190210151050.
- Erzaij, K. R. and Aljanabei, D. M. (2016) 'Performance Evaluation of the Investment Projects during the Implementation Phase (Najaf province as a case study)', *Journal of Engineering*, 22(8), pp. 54–74.
- Fayek, A. (1998) 'Competitive Bidding Strategy Model and Software System for Bid Prepapration', *Journal of Construction Engineering and Management*, 124(1), pp. 1–10. doi: 10.1061/(ASCE)0733-9364(1998)124:1(1).
- Gandomi, A. H. and Roke, D. A. (2015) 'Assessment of artificial neural network and genetic programming as predictive tools', *ADVANCES IN ENGINEERING SOFTWARE*. Elsevier Ltd, 88, pp. 63–72. doi: 10.1016/j.advengsoft.2015.05.007.
- Goh, Y. M. and Chua, D. (2013) 'Neural network analysis of construction safety management systems: a case study in Singapore', *Construction Management and Economics*, 31(5), pp. 460–470. doi: 10.1080/01446193.2013.797095.
- Hatush, Z. *et al.* (1997) 'Evaluating contractor prequalification data : selection criteria and project success factors Evaluating contractor prequalification data : selection criteria and project success factors', *Construction Management and Economics*, 15(2), pp. 129–147. doi: 10.1080/01446199700000002.
- Hua, G. B. (1996) 'Residential construction demand forecasting using economic indicators: A comparative study of artificial neural networks and multiple regression', *Construction Management and Economics*, 14(1), pp. 25–34. doi: 10.1080/01446199600000004.
- Huang, W. *et al.* (2013) 'Automation in Construction Contractor financial prequalifi cation using simulation method based on cashflow model', 35, pp. 254–262. doi: 10.1016/j.autcon.2013.05.004.
- Huang, W. *et al.* (2014) 'Dynamic Threshold Cash Flow–Based Structural Model for

Contractor Financial Prequalification', *Journal ofConstruction Engineering and Management*, 140(10), pp. 1–10. doi: 10.1061/(ASCE)CO.1943-7862.0000902.

- Hung-wei, C. and Ching-hung, L. (2017) 'Prediction of machining accuracy and surface quality for CNC machine tools using data driven approach', *Advances in Engineering Software*. Elsevier Ltd, 0, pp. 1–12. doi: 10.1016/j.advengsoft.2017.07.008.
- Ioannou, P. G., Asce, M. and Awwad, R. E. (2010) 'Below-Average Bidding Method', *Journal of Construction Engineering and Management*, 136(9), pp. 936–947.
- Jato-espino, D. *et al.* (2014) 'A review of application of multi-criteria decision making methods in construction', *Automation in Construction*. Elsevier B.V., 45, pp. 151–162. doi: 10.1016/j.autcon.2014.05.013.
- Jha, K. N. and Chockalingam, C. T. (2011) 'Prediction of schedule performance of Indian construction projects using an artificial neural network', *Construction Management and Economics*, 29(9), pp. 901–911. doi: 10.1080/01446193.2011.608691.
- Kadhim, S. N. and Erzaij, K. R. (2020) 'A Neural Network Model for Financial Performance Prediction : The Case for Road Works in Bahrain', *Test engineering and management*, 82(Jan-Feb), pp. 1589–1599.
- Khanzadi, M., Nasirzadeh, F. and Dashti, M. S. (2018) 'Fuzzy Cognitive Map Approach to Analyze Causes of Change Orders in Construction Projects', *Journal of Construction Engineering and Management*, 144(2004), pp. 1–12. doi: 10.1061/(ASCE)CO.1943-7862.0001430.
- Kuwaiti, E. Al, Ajmal, M. M. and Hussain, M. (2018) 'Determining success factors in Abu Dhabi health care construction projects: customer and contractor perspectives', *International Journal of Construction Management*, 18(5), pp. 430–445. doi: 10.1080/15623599.2017.1333401.
- Lam, K., Lam, M. C. and Wang, D. (2010) 'Efficacy of Using Support Vector Machine in a Contractor Prequalification Decision Model', *Journal of Computing in Civil Engineering*, 24(3), pp. 273–280.
- Lee, J. I. *et al.* (2018) 'Contractor Liquidity Evaluation Model for Successful Public Housing Projects', *Journal of Construction Engineering and Management*, 144(12), pp. 1–11. doi: 10.1061/(ASCE)CO.1943-7862.0001569.
- Li, H. and Love, P. E. D. (1997) 'Combining rule-based expert systems and artificial neural networks for mark-up estimation', *Construction Management and Economics*, 17(2), pp. 169–176. doi: 10.1080/014461999371664.
- Li, Y., Nie, X. and Chen, S. (2007) 'Fuzzy Approach to Prequalifying Construction Contractors', (January), pp. 40–49.
- Liu, Z. *et al.* (2018) 'Model of Equipment Sharing between Contractors on Construction Projects', *Journal of Con- struction Engineering and Management*, 144(6), pp. 1–11. doi: 10.1061/(ASCE)CO.1943-7862.0001485.
- Marzouk, M. M., El Kherbawy, A. A. and Khalifa, M. (2013) 'Factors influencing sub-contractors selection in construction projects', *HBRC Journal*. Housing and Building National Research Center, 9(2), pp. 150–158. doi: 10.1016/j.hbrcj.2013.05.001.
- Modin, Jö. (1995) 'Kbs-Class: A neural network tool for automatic content recognition of building texts', *Construction Management and Economics*, 13(5), pp.

411–416. doi: 10.1080/01446199500000046.

- Morfidis, K. and Kostinakis, K. (2017) 'Seismic parameters ' combinations for the optimum prediction of the damage state of R / C buildings using neural networks', *Advances in Engineering Software*. Elsevier Ltd, 106, pp. 1–16. doi: 10.1016/j.advengsoft.2017.01.001.
- Mundher, Z. *et al.* (2017) 'Predicting compressive strength of lightweight foamed concrete using extreme learning machine model', *Advances in Engineering Software*. Elsevier, (April), pp. 1–14. doi: 10.1016/j.advengsoft.2017.09.004.
- Nassar, K. and Hosny, O. (2013) 'Automation in Construction Fuzzy clustering validity for contractor performance evaluation : Application to UAE contractors', *Automation in Construction*. Elsevier B.V., 31, pp. 158–168. doi: 10.1016/j.autcon.2012.11.013.
- Nazari, A. *et al.* (2017) 'Fuzzy AHP Model for Prequalification of Engineering Consultants in the Iranian Public Procurement System', *Journal of Management in Engineerinagement in Engineering*, (1), pp. 1–13. doi: 10.1061/(ASCE)ME.1943-5479.0000489.
- Nguyen, L. D. *et al.* (2018) 'Effect of project complexity on cost and schedule performance in transportation projects', *Construction Management and Economics*. Routledge, 37(7), pp. 384–399. doi: 10.1080/01446193.2018.1532592.
- Odeyinka, H. A., Lowe, J. and Kaka, A. P. (2013) 'Artificial neural network cost flow risk assessment model', *Construction Management and Economics*, 31(5), pp. 423–439. doi: 10.1080/01446193.2013.802363.
- Ok, S. C. and Sinha, S. K. (2006) 'Construction equipment productivity estimation using artificial neural network model', *Construction Management and Economics*, 24(10), pp. 1029–1044. doi: 10.1080/01446190600851033.
- Partnerships, P. (2003) 'Project Asset Management for Pavement Assets under Performance-Based Contracts', *Advances in Public-Private Partnerships*, (Queiroz 1999), pp. 211–224.
- Plebankiewicz, E. (2012) 'Automation in Construction A fuzzy sets based contractor prequali fi cation procedure', *Automation in Construction*. Elsevier B.V., 22, pp. 433–443. doi: 10.1016/j.autcon.2011.11.003.
- Polat, G., Baytekin, S. and Eray, E. (2015) 'Mark-up size estimation in railway projects using the integration of AHP and Regression Analysis Techniques', *Procedia Engineering*. Elsevier B.V., 123, pp. 423–431. doi: 10.1016/j.proeng.2015.10.076.
- Rafiei, M. H. *et al.* (2018) 'Novel Machine-Learning Model for Estimating Construction Costs Considering Economic Variables and Indexes', *Journal of Construction Engineering and Management*, 144(2004), pp. 1–9. doi: 10.1061/(ASCE)CO.1943-7862.0001570.
- Rahman, M. M. (2014) 'Cost of Prequalification : A Pilot Study Cost of prequalification : a pilot study', *CRIOCM*, (February), pp. 1219–1229. doi: 10.1007/978-3-662-46994-1.
- Reuter, U., Sultan, A. and Reischl, D. S. (2018) 'A comparative study of machine learning approaches for modeling concrete failure surfaces', *Advances in Engineering Software*. Elsevier, 116(July 2017), pp. 67–79. doi: 10.1016/j.advengsoft.2017.11.006.
- Roberts, P. W. and Dowling, G. R. (2002) 'Corporate Reputation and Sustained Superior Financial Performance', *Strategic Management Journal*, 23(2002), pp. 1077–

1093. doi: 10.1002/smj.274.
- Russell, J. S. and Skibniewski, M. J. (1988) 'Decision Criteria in Contractor Prequalification', *Journal of Management in Engineering*, 4(2), pp. 148–164.
- Safa, M. *et al.* (2017) 'Construction contract management using value packaging systems', *International Journal of Construction Management*, 17(1), pp. 50–64. doi: 10.1080/15623599.2016.1167369.
- Shi, J. J. (1999) 'A neural network based system for predicting earthmoving production', *Construction Management and Economics*, 17(4), pp. 463–471. doi: 10.1080/014461999371385.
- Sivanandam, S. . and Paulraj, M. (2003) *Introduction to Artificial Neural Networks*. Reprint 20. New Delhi: Vikas Publishing Publishing House Pvt Ltd.
- Tah, J. H. M., Carr, V. and Howes, R. (1999) 'Information modelling for case-based construction planning of highway bridge projects', *Advances in Engineering Software*, 30, pp. 495–509.
- Tam, C. M. and Tong, T. K. L. (2003) 'GA-ANN model for optimizing the locations of tower crane and supply points for high-rise public housing construction', *Construction Management and Economics*, 21(3), pp. 257–266. doi: 10.1080/0144619032000049665.
- Taylor, P. *et al.* (2015) 'Using data envelopment analysis to support best- value contractor selection', *Journal of Civil Engineering and Management*, (September 2015). doi: 10.3846/13923730.2014.897984.
- Tordeux, A. *et al.* (2019) 'Prediction of pedestrian dynamics in complex architectures with artificial neural networks', *Journal of Intelligent Transportation Systems*. Taylor & Francis, 0(0), pp. 1–13. doi: 10.1080/15472450.2019.1621756.
- Wang, T. *et al.* (2014) 'Relationships among Risk Management , Partnering , and Contractor Capability in International EPC Project Delivery', *Journal ofManagement in Engineeringing*, pp. 1–10. doi: 10.1061/(ASCE)ME.1943-5479.0000459.
- Wanous, M., Boussabaine, H. A. and Lewis, J. (2003) 'A neural network bid/no bid model: The case for contractors in Syria', *Construction Management and Economics*, 21(7), pp. 737–744. doi: 10.1080/0144619032000093323.
- Wee, E., Wong, C. and Kyun, D. (2018) 'A simplified method to predict fatigue damage of TTR subjected to short- term VIV using artificial neural network', *Advances in Engineering Software*. Elsevier, 126(June), pp. 100–109. doi: 10.1016/j.advengsoft.2018.09.011.
- Xu, W. *et al.* (2017) 'Corroded pipeline failure analysis using artificial neural network', *Advances in Engineering Software*. Elsevier Ltd, 0, pp. 1–12. doi: 10.1016/j.advengsoft.2017.05.006.
- Zhang, S. *et al.* (2019) 'Effect of Level of Owner-Provided Design on Contractor ' s Design Quality in DB / EPC Projects', *Journal of Construction Engineering and Management*, 145(1), pp. 1–10. doi: 10.1061/(ASCE)CO.1943-7862.0001587.
- Zhou, G. *et al.* (2019) 'Deep learning enabled cutting tool selection for special-shaped machining features of complex products', *Advances in Engineering Software*. Elsevier, 133(28), pp. 1–11. doi: 10.1016/j.advengsoft.2019.04.007.