Seventh International Conference on Construction in the 21st Century (CITC-VII)
"Challenges in Innovation, Integration and Collaboration in Construction & Engineering"
December 19-21, 2013, Bangkok, Thailand

A Comparative Study of Classification Methods for Contractor Prequalification Models

Evren Ülkeryıldız Serdar Kale
İzmir Institute of Technology, Department of Architecture, İzmir, Turkey
evrenulkeryildiz@iyte.edu.tr

Serdar Kale
İzmir Institute of Technology, Department of Architecture, İzmir, Turkey
serdarkale@iyte.edu.tr

Abstract

Contractor prequalification has been an important issue in construction business practice and academic research studies for quite a long time. The main objective of contractor prequalification is to differentiate contractors that have the necessary financial, physical, and human resources to undertake construction work for those that do not have such resources. This objective is commonly achieved by using either statistics-based or machine learning-based classification methods. A succinct review of previous contractor prequalification models revealed that there is no comparative study available in the construction management literature for evaluating the relative performance of the various classification methods. The research presented in this paper addressed this missing research issue by using simulation experiments to compare the relative classification performances of logistic regression (LR), artificial neural networks (ANNs), and support vector machines (SVMs) for the combinations of two different data characteristics, i.e., 1) the strength of correlation between input variables and 2) the complexity of the functional relationships between input variables and the output variable. The results of the simulations suggested that SVMs consistently outperformed ANNs and LR.

Keywords: Contractor prequalification, statistical, machine learning, performance, classifiers.

1. Introduction

Mitigating contractual hazards (e.g., cost overruns, schedule delays, quality and functionality that do not meets the owners' expectations, lawsuits, and defaulted contractors and subcontractors) in organizations that conduct construction projects has been a subject of numerous research streams in the literature (Holt, 1998; Waara, 2008; Schatteman et al., 2008; Badenfelt, 2011). The selection of transaction partners (i.e., contractors, subcontractors, material vendors) is one of the primary means to mitigate contractual hazards in the construction industry, just as it is in any other industry. As a rational response to the needs of the social entities of the construction industry, construction management scholars have been involved in developing prequalification models for the use of clients (Hatush & Skitmore, 1998; Khosrowshahi, 1999; Lam et al., 2001; El-Sawalhi et al., 2007; Darvish et al., 2009; Nieto-Morote & Ruz-Vila, 2012), contractors (Ko et al., 2007; Arslan et al., 2008), and sureties (Awada & Fayek, 2012). A succinct review of the literature revealed that the majority of the previous models used to select transaction partners were developed for the use of clients (Hatush & Skitmore, 1998; Khosrowshahi, 1999; Lam et al., 2001; El-Sawalhi et al., 2007; Darvish et al., 2009; Nieto-Morote & Ruz-Vila, 2012). The different clients of the construction industry, i.e., public, private, experienced, inexperienced, and once-in-a-lifetime clients, face significant contractual hazards in their transactions with contractors mainly due to high degree of uncertainty and asset specifity involved in these transactions. Contractor prequalification enables clients to mitigate contractual hazards by eliminating incompetent, underfinanced, inexperienced contractors from further consideration. It also enables contractors to benchmark their financial status and technical abilities externally and, in turn, improve their performance during construction. Contractor prequalification is a binary classification (i.e., qualified or unqualified) problem.

Different classification methods have been used to develop contractor prequalification models. The extant literature clearly indicates that the performances of these classification methods have been an important issue. In the literature related to construction management, it is very common to find various arguments or conclusions, e.g., (1) the cluster analysis method has the highest potential for contractor prequalification problems (Holt, 1998), (2) artificial neural networks produce the best predictive performance for contractor prequalification problems (El-Sawalhi, Eaton, & Rustom, 2007), and (3) support vector machines produce better performance than artificial neural networks and logistic regression models (Lam et al., 2009). Yet, the majority of such arguments or conclusions is based on either intuition or the real data sets collected from construction clients through questionnaire surveys rather than properly designed simulation experiments. Also, it is acknowledged extensively in the literature that there is not necessarily a single best classification method; rather, the best performing classification method depends on the characteristics of the dataset to be analyzed. In the light of this background, it is evident that a study based on properly-designed simulation experiments for the classification methods used in the past prequalification models under various combinations of data characteristics is a topical issue that has remained unaddressed in the literature concerning construction management. The study presented in this paper was intended to address this topical issue in the context of contractor prequalification models. Its primary objectives were (1) to explore the influence of the characteristics of the dataset (i.e., the strength of correlation between input variables and model complexity) on the performance-classification methods in the context of contractor prequalification problems and (2) to guide construction management researchers in the selection of the optimal classification method using a given dataset of characteristics.

2. Contractor Prequalification

Contractor prequalification is the process of screening contractors to construct a pool (sample) of competitive, competent, and capable contractors from which tenders can be requested for the subsequent award of the construction contract (Lam et al., 2005). The primary objectives of the contractor prequalification include (1) eliminating incompetent and unresponsive contractors, (2) enhancing opportunities for competent and responsive contractors, (3) creating fair competition among competent and responsive contractors, and (4) achieving balance between price competition and project performance. Contractor prequalification is a binary classification problem. Even so, some construction management scholars have approached the contractor prequalification problem as a ranking problem and used multi-criteria decision-making models, such as the analytical hierarchy process (Anagnostopoulos & Vavatsikos, 2006), the analytical network process (Cheng & Li, 2004), evidential reasoning (Sönmez et al., 2002). Some other construction management scholars have assumed that contractor prequalification is a utility problem and have applied multi-attribute analysis (Holt et al., 1994) or multi-attribute utility theory concepts to contractor prequalification problems (Hatush & Skitmore, 1998). Only a few construction management scholars have approached the contractor prequalification problem as a classification problem and used classification methods, such as cluster analysis (Holt, Classifying construction contractors: a case study using cluster analysis, 1997), logistic regression (Wong, 2004), unsupervised-learning neural networks (Elazouni, 2006), supervised artificial neural networks (Khosrowshahi, 1999; El-Sawalhi et al., 2007), and support vector machines (Lam et al., 2009).

3. Classification Methods

Classification probably is one of the oldest problems of humankind. It involves the process of assigning observations (i.e., objects, social entities) into one of a set of groups based on their attributes. Classification has been used extensively in addressing and solving a variety of practical problems in various research fields (e.g., basic science, applied science, and social sciences). The primary objective of classification is to group observations correctly into two or more mutually-exclusive groups. Several grouping schemes have been proposed for studying classification methods, such as (1) supervised vs. unsupervised classification methods (Hastie et al., 2008) and (2) statistics vs. machine learning-based classification methods. Supervised classification methods (e.g., linear discriminant analysis, quadratic discriminant analysis, logistic regression, and support vector machines) involve assigning future observations correctly to groups that are already known to exist (Johnson & Wichern, 2002). Conversely, unsupervised classification methods (e.g., cluster analysis and unsupervised artificial neural networks) involve the process of assigning observations to groups that are not known a priori. Statistics-based classification methods, also known as classical classification methods, subsume a number of methods that differ with respect to their assumptions (e.g., group distribution and functional form of the discrimination). Statistics-based classification models that have strict assumptions, such as normality and linearity, are viewed as fully-parametric classification models, whereas models that have less restrictive assumptions are viewed as semi-parametric (e.g., k-nearest neighborhood, linear programming, and logistic regression). Machine learning-based classification models are less restrictive and do not require such assumptions (normality and linearity). A review of the classification methods used in past prequalification models indicated that the most commonly used statistics-based classification method is logistic regression, whereas the most commonly used machine-learning methods are artificial neural networks (ANNs) and support vector machines. The following section presents an overview of these three classification methods.

3.1 Logistic Regression

Logistic regression is a semi-parametric, statistics-based classification method that is commonly used to predict the probability of the occurrence of a dichotomous variable from one or more independent (i.e., exploratory factors) variables. It uses odds and the logistic transformation of odds to link the probability of occurrence or non-occurrence of a dichotomous variable (e.g., contractor being prequalified or disqualified) to the independent variables (e.g., prequalification criteria). The odds are the ratio of the probability of occurrence to the probability of non-occurrence of a dichotomous variable:

$$Odds = \left(\frac{P}{1-P}\right) \quad [1]$$

where P is the probability of occurrence. The logistic transformation for the odds of the occurrence of a dichotomous variable can be written as:

$$P = \left(\frac{1}{1+exp^{-(\alpha+\sum_{i=1}^{k}\beta_i x_i)}}\right) \quad [2]$$

where x_i (i = 1, 2, …, k) is the i^{th} independent variable, α is a constant, and β_i is the coefficient of the i^{th} independent variable. A cutoff value of 0.50 is commonly used in logistic regression models.

3.2 Artificial Neural Networks

Artificial neural network models are powerful, flexible, and intuitive data analysis approaches for capturing and identifying the complex relationships between input/independent variables and output/ dependent variables. An artificial neural network consists of (1) an input layer, (2) an output layer, and (3) one or more hidden layers. Each layer comprises one or more neuron and each neuron is linked to the other neurons in neighboring layers by varying weight coefficients. A neuron receives input signals, processes those signals, and delivers a single output. The following tasks are performed by a neuron in processing its input signals: (1) receiving input signals from other neurons, (2) multiplying input signals by corresponding weights, (3) summing weighted input signals, (4) transforming the computed sum by a transfer function, and (5) sending the transformed sum to other neurons. In mathematical terms, this process for neuron j can be described by the following equations (Russell and Norvig, 2003):

$$v_j = \sum_{k=1}^{m} w_{ji} * x_i + b_j, \qquad [3]$$

where v_j is the net input to neuron j, x_i is the incoming signal from neuron i, w_{ji} is the weight associated with the input from neuron i, n is the number of neurons in preceding layer, and b_j is the bias associated with neuron j.

$$y_j = \varphi(v_j), \qquad [4]$$

where y_j is the output of neuron j (also termed as the activation value of neuron j), and φ is an activation function to generate the outgoing signal of neuron j. Activation functions (φ) can be linear or non-linear, such as an identity, hyperbolic tangent, logistic, exponential, sine, or Gaussian function.

3.3 Support Vector Machines

Support vector machines, like artificial neural networks, use supervised learning algorithms. A support vector machine is a type of maximal margin classifier that aims to construct an optimal separating hyperplane, f(x), that maximizes the margin between the two classes, $y_i \epsilon \{-1,1\}$. For a linearly separable classification problem, the optimal separating hyperplane can be defined as (Vapnik, 1998):

$$f(x) = w * x_i + b = \sum_{k=1}^{m} w_k * x_k + b = 0, \qquad [5]$$

where x_i is the n-dimensional input vector ($x_i \epsilon R^n$), w is the normalized weight vector, and b is the normalized bias term. Any optimal separating hyperplane should satisfy the following constraint:

$$y_i * (w * x_i + b) \geq 1 \qquad [6]$$

In many real-world problems, data are not linearly separable, which is due mainly to nonlinearity, noise, and contamination. In such cases, an optimum separating hyperplane cannot be constructed without error. Support machine vectors use (1) the *soft margin method* or (2) the *kernel function method* to address this issue. Soft margin method-based support vector machines introduce the slack variable into Equation 7:

$$y_i * (w * x_i + b) \geq 1 - \zeta_i, \quad \zeta_i \geq 0, i = 1,2 \ldots m, \qquad [7]$$

where ζ_i is the positive slack variable that specifies the distance from the upper and lower boundary of the optimum separating hyperplane (i.e., soft margin). The construction of the optimal separating hyperplane can be expressed as the following optimization problem:

$$Minimize: \frac{1}{2}\|w\| + C\sum_{i=1}^{N} \zeta_i \qquad [8]$$

$$Subject\ to: y_i * (w * x_i + b) \geq 1 - \zeta_i, \quad \zeta_i \geq 0,$$

where C is a positive constant that determines the trade-off between classification error and the margin. Equation 9 can be solved more easily by introducing the Langrange multipliers α_i and α_j:

$$Maximize\ L(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j \langle x_i \cdot x_j \rangle \qquad [9]$$

$$Subject\ to \sum_{i=1}^{m} \propto_i y_i = 0, \quad \propto_i \geq 0, \ i = 1, \ldots, m,$$

where $\langle x_i \cdot x_j \rangle$ is the inner product of $x_i \cdot x_j$. Finally, the linear optimization function for the optimum separating hyperplane can be written as:

$$f(x) = sign\left(\sum_{i,j=1}^{m} \alpha_i y_i (x_i, x_j) + b\right) \qquad [10]$$

Kernel method-based SVM maps the original input data into a much higher dimensional feature space by using a non-linear mapping function, Ø(x), and then constructs the optimal separating hyperplane in this feature space similar to the one used in the linearly-separable classification problem.

$$f(x) = sign\left(\sum_{i,j=1}^{m} \alpha_i y_i (\emptyset x_i, \emptyset x_j) + b\right) \qquad [11]$$

Yet, selecting an appropriate non-linear function, Ø(x), and the computation of the inner product of $\langle \emptyset x_i \cdot \emptyset x_j \rangle$ in the feature space can easily become computationally challenging or even infeasible to perform. This computational challenge can be overcome by substituting the inner product of $(\emptyset x_i, \emptyset x_j)$ with a kernel function $K(x_i, y_j)$. The optimization problem of finding the optimum separating hyperplane in a high-dimensional feature space by using a kernel function can be defined as:

$$f(x) = sign\left(\sum_{i,j=1}^{m} \alpha_i y_i K(x_i y_j) + b\right) \qquad [12]$$

Support vector machines use different kernel functions, such as (1) linear kernel functions, (2) polynomial kernel functions, (3) sigmoid kernel functions, and (4) radial basis functions (RBFs). Each kernel function has one or more parameters that must be optimized. The radial basis function, also known as Gaussian kernel, is the most common kernel function used in support vector machines due its classification ability and relatively lower computation load. Radial basis kernel function can be defined as:

$$K(x_i y_j) = \exp\left(-\frac{\|x_i - y_j\|^2}{\gamma^2}\right) \qquad [13]$$

where γ is the user-defined width parameter of the Radial basis kernel.

4. Data and Methods

In the research presented in this paper, a number of simulation experiments were conducted to compare the performance of one statistics-based classification method, i.e., Logistic Regression (LR), and two machine-learning based methods, i.e., artificial neural networks (ANNs) and support vector machines (SVMs), in the context of the contractor prequalification problem. The impacts of correlation levels between input variables (Ω) and model complexity on the classification method were analyzed by the generation of simulated data. In the simulations, a sample size of 500 observations (N = 500), 10 input variables (x_i, i = 1, 2 …, k, and k = 10), one binary output variable (i.e., qualified and unqualified), and three different correlation levels (Ω) between input variables and three levels of model complexity were used. A total of nine data sets (i.e., three correlation levels and model complexity levels: 3X3) were generated through simulations. Each simulated data set consisted of 500 observations and had 10 input variables (x_i), which were generated from a multivariate normal distribution with a mean of 0 ($\mu = 0$), a standard deviation of 1 ($\sigma = 1$), and a pre-defined correlation level (Ω) between input variables. The three different correlation levels (Ω) used in the simulations were (1) weak, (2) moderate, and (3) strong. The correlation levels between input variables ranged from 0.05 to 0.30 for the weak correlation level, 0.40 to 0.60 for the moderate correlation level, and 0.70 to 0.90 for the strong correlation level. Three levels of model complexity were analyzed by assuming that the true relationship between the 10 input variables (x_i) and the binary output (y) was a logistic function. The complexity levels of the models used in the simulations increased in the following order: (1) linear model, (2) simple model, and (3) complex model.

For the linear model:

$$logit(y) = \alpha + \sum_{i=1}^{10} \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \varepsilon \qquad [14]$$

For the simple model:

$$logit(y) = \alpha + \sum_{i=1}^{10} \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_2 x_7 + \beta_{12} x_3 x_8 + \beta_{13} x_5 x_{10} + \varepsilon \qquad [15]$$

For the complex model:

$$logit(y) = \alpha + \sum_{i=1}^{10} \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_1^2 + \beta_{12} x_4^3 + \beta_{13} x_7^4 + \varepsilon \qquad [16]$$

The parameters of artificial neural networks (i.e., the number of hidden layers, the number of neurons in the hidden layers, and the activation functions for the input and output layers) and support vector machines (i.e., capacity and the width parameter of the Radial basis kernel) were optimized for each simulated data set to provide the best classification accuracy. The classification accuracies of logistic regression, artificial neural networks, and support vector machines in each simulation were evaluated by using the receiver operating characteristics (ROC) curve method. The ROC curve method is a simple, but powerful, test to evaluate the discrimination performance of a binary classification method. It has been used extensively in previous studies to compare the accuracies of classification methods. The ROC curve method, which is based on signal processing theory, is a plot of *sensitivity* versus *1-specifity* evaluated at different cut-off points of a parameter. *Sensitivity*, also known as true positive rate (TPR), is a measure of positive cases (i.e., prequalified contractors) being correctly identified as positive cases (i.e., prequalified contractors) by a classification method. *Specificity*, also known as true negative rate (TNR), is a measure of negative cases (i.e., unqualified contractors) being correctly identified as negative cases (unqualified contractors) by a classification method. The area under the ROC curve ranges 1 to 0.5, with a value of 1.0 indicating perfect discriminatory power and a value of 0.5 indicating poor classification performance.

5. Results

Table 1 presents the values for the area under the ROC curves for logistic regression, artificial neural networks, and support vector machines by model complexity and correlation strength. It is clear from Table 1 that the level of complexity of the model and the strength of the correlations between input variables jointly affect the classification performance of logistic regression, artificial neural networks, and support vector machines. Support vector machines have the highest values for the area under the ROC curve, followed by artificial neural networks and logistic regression, in that order. The values of the area under the ROC curve for logistic regression ranged from a minimum of 0.51 for the complex model with moderately-correlated input variables to a maximum of 0.97 for the linear model with strongly-correlated input variables. It also was evident from the values of the area under the ROC curve that the classification performance of logistic regression decreased drastically as the complexity of the models increased and the strength of the correlations between the input variables decreased. Similar observations also were made for artificial neural networks and support vector machines, but the decreases in their classification performances were not as drastic as in the case of logistic regression. Furthermore, it appeared that the classification performance of logistic regression was almost as good as those of artificial neural networks and support vector machines when the input variables were correlated strongly with each other and had linear relationships with the output variables. Table 1 also points out that the classification performances of support vectors machines were marginally better than those of artificial neural networks for both linear and simple models. Yet, the classification performances of support vector machines for the complex models with weak, moderate, and strong correlation levels were significantly better than those of artificial neural networks.

Table 1: Values of Areas Under the ROC Curves for Classification Methods by Model Complexity and Correlation Level

Model Complexity	Correlation Level	Method		
		LR	ANN	SVM
Linear	Weak	0.93**	0.94**	0.96**
	Moderate	0.96**	0.98**	0.98**
	Strong	0.98**	0.99**	0.99**
Simple	Weak	0.80**	0.84**	0.85**
	Moderate	0.81**	0.85**	0.89**
	Strong	0.88**	0.90**	0.92**
Complex	Weak	0.53	0.71*	0.76*
	Moderate	0.50	0.67*	0.74*
	Strong	0.56	0.67*	0.79**

*p≤0.01 and **≤0.05

It is clear from the results of the simulation experiments that logistic regression has the lowest classification performance under the various combinations of data characteristics, whereas artificial neural networks and support vector machines demonstrated relatively high classification performance, albeit with two major challenges. First, the classification performances of these two models depended critically on their parameters being set correctly, i.e., kernel parameters for SVM and, for ANN, the number of hidden layers, the number of neurons in the hidden layers, and the activation functions. Second, the relative importance of input variables used in the models cannot be interpreted or inferred easily without conducting additional analyses. Conversely, logistic regression had the greater ease of use and simplicity in interpreting its results (i.e., coefficients of input variables and odds). Therefore, construction management researchers who are planning to develop a contractor prequalification model should be aware of the trade-off between classification performance of a model and interpretability of the results provided by that model.

6. Conclusions

For decades, contractor prequalification has been an important issue in the construction management research and construction business practice. It is commonly conceptualized as a binary classification problem, and various classification methods, including logistic regression, artificial neural networks, and support vector machines, have been used to develop contractor prequalification models. Previous models predominantly have used survey data either to develop a contractor prequalification model or to compare one classification method with others. In the research described in this paper, a systematic approach was used to compare the classification performance of three classification methods under various combinations of data characteristics. Several simulation experiments were conducted to explore the impact of data characteristics on the classification performance of logistic regression, artificial neural networks, and support vector machines. The results indicated that the support vector machine provided the best performance under all of the combinations of data characteristics that were studied in the simulation experiments. The results of the simulation experiments suggest that, among the three classification methods that were evaluated, support vector machines may be the best for addressing contractor prequalification problems. One promising future research avenue would be to extend the scope of the simulation experiments to include the assessment of the effects of other data characteristics, such as sample size, variance of the input variables, and group size ratio, on the classification performances of logistic regression, artificial neural networks, and support vector machines.

7. References

Anagnostopoulos, K. P. and Vavatsikos, A. P. - *An AHP model for construction contractor prequalification*. Operational Research, vol. 6/3, (2006), pp. 333-346.

Arslan, G., Kıvrak, G., Birgönül, T. and Dikmen, İ.. - *Improving sub-contractor selection process in construction projects*. Automation in Construction, vol. 17/4, (2008), pp. 480–488.

Awada, A. and Fayek, A. R. - *A decision support system for contractor prequalification for surety bonding*. Automation in Construction, vol. 21/1, (2012), pp. 89–98.

Badenfelt, U. - *Fixing the contract after the contract is fixed: A study of incomplete contracts in IT and construction projects*. International Journal of Project Management, vol. 29/5, (2011), pp. 568–576.

Cheng, E. W. and Li, H. - *Contractor selection using the analytic network process*. Construction Management and Economics, vol. 22/10, (2004). pp. 1021-1032.

Darvish, M., Yasaei, M. and Saeedi, A. - *Application of the graph theory and matrix methods to contractor ranking*. International Journal of Project Management, vol. 27/6, (2009), pp. 610-619.

Elazouni, A. - *Classifying Construction Contractors Using Unsupervised-Learning Neural Networks*. Journal of Construction Engineering and Management, vol. 132/12, (2006), pp. 1242-1253.

El-Sawalhi, N., Eaton, D. and Rustom, R. - *Contractor prequalification model: State-of-the-art*. International Journal of Project Management, vol. 25/5, (2007), pp. 465-474.

Hastie, T., Tibshirani, R. and Friedman, J. - *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer-Verlag, New York, 2008.

Hatush, Z. and Skitmore, M. R. - *Contractor selection using multi-criteria utility theory: An additive model*. Building and Environment, vol. 3/2-3, (1998), pp. 105-115.

Holt, G. D. - *Classifying construction contractors: a case study using cluster analysis*. Building Research and Information, vol. 25/6, (1997), pp. 374-382.

Holt, G. D. - *Which contractor selection methodology?* International Journal of Project Management. Vol. 16/3, (1998), p. 153–164.

Holt, G. D., Harris, F. C. and Olomolaiye, P. O. - *Applying multi-attribute analysis to contractor selection decisions*. European Journal of Purchasing and Supply Management, vol. 1/3, (1994), pp. 139–148.

Johnson, R. and Wichern, D. - *Applied Multivariate Statistical Analysis*. Prentice Hall, Upper Saddle River, New Jersey, 2002.

Khosrowshahi, F. - *Neural network model for contractors' prequalification for local authority projects*. Engineering, Construction and Architectural Management, vol. 6/3, (1999), pp. 315-328.

Ko, C. H., Cheng, M. Y. and Wu,T. K. - *Evaluating sub-contractors performance using EFNIM*. Automation in Construction, vol. 16/4, (2007), pp. 525–530.

Lam, K. C., Hu, T. S. and Ng, S. T. - *Using the principal component analysis method as a tool in contractor pre-qualification*. Construction Management and Economics, vol. 23/7, (2005), pp. 673-684.

Lam, K. C., Hu, T. S., Ng, S. T., Skitmore, R. M. and Cheung, S. O. - *A fuzzy neural network approach for contractor prequalification*. Construction Management and Economics, vol. 19/2, (2001), pp. 175-188.

Lam, K., Palaneeswaran, E. and Yu, C. Y. - *A support vector machine model for contractor prequalification*. Automation in Construction, vol. 18/3, (2009), pp. 321-329.

Nieto-Morote, A. and Ruz-Vila, F. - *A fuzzy multi-criteria decision-making model for construction contractor prequalification*. Automation in Construction, vol. 25/8, (2012), pp. 8-19.

Schatteman, D., Herroelen, D. W. and Van de Vonder, S. - *Methodology for integrated risk management and proactive scheduling of construction projects*. Journal of Construction Engineering and Management, Vol. 134/11, (2008), pp. 858-893.

Sönmez, M., Holt, G. D., Yang, J. B. and Graham, D. - *Applying evidential reasoning to prequalifying construction contractors*. Journal of Management in Engineering, vol. 18/3, (2002), pp. 111-119.

Vapnik, V. N. - *Statistical Learning Theory*, Springer, New York, 1998.

Waara, F. - *Mitigating contractual hazards in public procurement: a study of Swedish local authorities*. Construction Management and Economics, Vol. 26/2, pp. 137-145, (2008).

Wong, H. C. - *Contractor performance prediction model for the united kingdom construction contractor: Study of logistic regression approach*. Journal of Construction Engineering and Management, vol. 130/5, (2004), pp. 691-698.