Modelling of Construction Project Management Effectiveness by Applying Neural Networks

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Abstract: The paper presents modelling of construction project management effectiveness from the perspective of construction management organization. Construction projects performance data from construction management companies in Lithuania and the United States of America was collected and used for model development. Construction project management effectiveness model (CPMEM) was established by using artificial neural networks (ANNs). Twelve key determinants factors were determined, that could increase opportunity to improve organizational performance through more effective project management. Construction project management effectiveness model and its application algorithm are recommended as a decision-support tool for competitive bidding to evaluate management risk of a construction project. The model allows construction project managers to focus on the key project management effectiveness factors, reduce the level of construction management risk and provide substantial savings for construction management company.

Keywords: Construction Project Management, Neural Networks.

1. Introduction

Construction projects are delivered under conditions of risk in the competitive market environment. There are external risks (economic, political, financial and environmental) and internal risks based on project management issues, i.e. projects manager's and his team competency, experience, strategic and tactic decisions made during construction project delivery. The opportunity to improve organizational performance through more effective project management could provide substantial savings for construction management company.

Traditionally, construction project management effectiveness is defined as the degree to which project goals and expectations are met. It should be viewed from respective perspectives of different project participants and the goals related to a variety of elements, including technical, financial, social and professional issues. Criteria are needed to compare the goal level against the performance level. The criteria are the set of principles or standards by which judgment is made (Lim et al. 1999). While effectiveness is measured in terms of goal attainment, there is ambiguity in determining whether a project is success or failure.

Project management effectiveness depends on the certain factors of project management system. The literature review revealed a substantial volume of work on measuring or identifying the factors or conditions contributing to the effectiveness of construction projects.

There are three main trends of previous research on construction project success factors:

- key factors identification for construction project success (Ashley et al., 1987; Pinto at al., 1988; Jaselskis et al., 1991; Sanvido et al., 1992; Chua et al., 1997; Chua et al., 1999; Millet, 1999);
- identification of key success factors for a particular group of construction projects, e.g. BOT, design-build (Mohsini et al., 1992; Tiong, 1996; Molenaar et al., 2001; Chan et al., 2001, Zhang, 2005; Shen et al., 2005);
- analysis of a particular factor impact on construction project success (Faniran et al., 1998; Angelides, 1999; Cheng et al., 2000; Back et al., 2000; Mitropoulos et al., 2000; Bower et al., 2002; Ford, 2002, Jan et al., 2002).

Some writers were attempting to develop predictive models while others focused on generating a list of practices. Predictive models developed to identify the key factors and to measure their impact on overall project success were using regression and correlation techniques, factor analysis, Monte-Carlo simulation, experts and multicriteria decision-making support methods. Essentially in these approaches the functional relationships between the input factors and project outcome is assumed and tested against the data. The relationships are modified and retested until the models that best fit the data are found.

When developing construction project management effectiveness model (CPMEM) referred to here, the writers attempted to cull the best aspects of artificial neural networks (ANN) methodology. The neural network approach does not require an a priori assumption of the functional relationship. Artificial neural networks are very useful because of their functional mapping properties and the ability to learn from examples. Multilayer neural networks have been shown to have a certain "universal" approximation property. Networks have been compared with many other functional approximation systems and found to be competitive in terms of accuracy (Haykin, 1999). This and the ability to learn from examples allow modelling the complex construction project management system where behavioural rules are not known in detail and are difficult to analyse correctly.

2. Modelling of Construction Project Management Effectiveness by Applying Neural Networks

The foundation of the artificial neural networks (ANNs) paradigm was laid in the 1950s, and ANNs have gained significant attention in the past decade because of the development of more powerful hardware and neural algorithms (Haykin 1999). Artificial neural networks have been studied and explored by many researchers where they have been used, applied, and manipulated in almost every field. As in civil engineering and management applications, neural networks have been employed in different studies. Some of these studies cover the mathematical modelling of non-linear structural materials, damage detection, non-destructive analysis, earthquake classification, dynamical system modelling, system identifications, and structural control of linear and non-linear systems, construction productivity modelling, construction technology evaluation, cost estimation, organisational effectiveness modelling and others (Adeli et al., 1998; Lu et al., 2000; Sinha et al., 2000).

Among the numerous artificial neural networks that have been proposed, backpropagation networks have been extremely popular for their unique learning capability. 80% of practical ANN applications used the backpropagation neural networks (Haykin 1999). The authors of the paper applied backpropagation neural networks methodology to create the model of construction project management effectiveness.

Modelling of construction project management effectiveness by applying backpropagation neural networks consists of the following stages:

- selection of the variables of the construction project management effectiveness neural network model (CPMEM);
- selection and preparation of training data for the CPMEM;
- designing and training the construction project management effectiveness neural network;
- evaluation of the importance of a particular input factor to the CPMEM output by applying sensitivity analysis technique;
- identification of the key construction project management effectiveness factors and modification of the CPMEM;
- determining the validation range of the CPMEM practical applications.

The construction project management effectiveness neural network model had been developed using *NEURAL NETWORKS TOOLBOX* by *MATLAB*. Preparation of the training data and statistical computations had been performed by applying *Microsoft Excel.*

2.1 Questionnaire Survey and Data Analysis

A questionnaire was developed to collect data from past projects to be used in developing a predictive model. The framework for the list of construction management effectiveness factors covering areas related to project manager, project team, project planning, organisation and control was selected from the research conducted by Jaselskis and Ashley (1991). However, the actuality of each construction management factor was retested by interviewing construction management practitioners and the approach was modified according to the interviewers' opinion. Construction project management effectiveness factors described in Table 1 served as the independent input variables of the CPMEM.

Construction cost variation criterion was used to measure construction project management effectiveness. The output variable of that model - construction project cost variation Q - was calculated by equation:

$$Q = \frac{PI - FI}{PI} \cdot 100\% \qquad (1)$$

where PI - estimated construction project cost; FI - actual construction project cost.
The present study is based on a set of data obtained in a questionnaire survey on construction project management effectiveness factors from construction management organizations in Lithuania and the USA. Personal contact was the major communication tool used to get organizations participated in the study. The interviewees were construction and project managers. Twelve Lithuanian companies participated in the research and presented information on 32 completed construction projects. The average size for the projects is 4.3 million Litas (1.6 million USD) and the mean duration is 7 months. Twenty seven US construction management companies presented information on 54 completed construction projects with the average size of 30.1 million USD and the mean duration of 14 months. Statistical analysis calculations proved that random project samples obtained from two countries belong to the same statistical population. Then the whole data set of 86 projects was divided into two subsets: training and testing. The neural network model was trained with 76

project samples and retested with 10 project samples. The testing subset represented 10 different construction companies and all 5 construction cost variation classes.

Table 1: Construction project management effectiveness factors

Category	Project management factor	*Measure*	*Priority*
Project manager (PM)	PM meetings	Number /month	7
	PM time devoted	Hours/day	16
	PM site visits	Number/month	2
	PM subordinates	Number	10
	PM levels to craftsmen	Number	8
	PM education level	Years	11
	PM construction experience	Years	27
	PM project management experience	Years	15
	PM scope experience	Number of projects	12
	PM technical experience	Number of projects	13
	PM scope experience other than as PM	Number of projects	9
	PM technical experience other than as PM	Number of projects	14
Project team	Team turnover	Percent per year	26
	Monetary incentives	% of total construction cost	1
Planning	Design complete at construction start	Percent	21
	Activities in execution plan	Number	19
	Budget contingency	Percent	18
	Independent constructability analysis	% of total construction cost	5
	Modularization	% of total construction cost	4
Organization and control	Progress inspection	Number/month	23
	Quality inspection	Number/month	22
	Safety inspection	Number/month	17
	Control system budget	% of total construction cost	3
	Design control meetings	Number/month	20
	Construction control meetings	Number/month	24
	Schedule updates	Number/month	6
	Budget updates	Number/month	25

A neural network works best when all its inputs and outputs vary within the range 0 and 1. Thus all the data were classified and massaged before using them in a neural network. The input data - project management factors - were classified into six groups and the output data - the percentage of the construction cost variation in loss or profit - were classified into five groups (Table 2).

Table 2: Classification of project cost variation

Range of predicted project cost variation Q	Class description	Predicted neural network output
Q > +10%	Very good	00001
+3% < Q ≤ +10%	Good	00010
–3% ≤ Q ≤ +3%	Average	00100
–10% ≤ Q < –3%	Poor	01000
Q< –10%	Very poor	10000

2.2. Designing and Training of Neural Network Model

The neural network chosen in the present study is multilayered with neurons in all layers fully connected in the feedforward manner (Fig. 1). Sigmoid function is used as an activation function. The number of neurons in the input and output layer was decided by the number of input and output variables of the construction project management effectiveness neural network. Thus, the input layer had 27 neurons and the output layer had 5 neurons, representing five classes of the construction cost variation. One hidden layer is chosen in which the number of neurons is decided during the training process by trial and error.

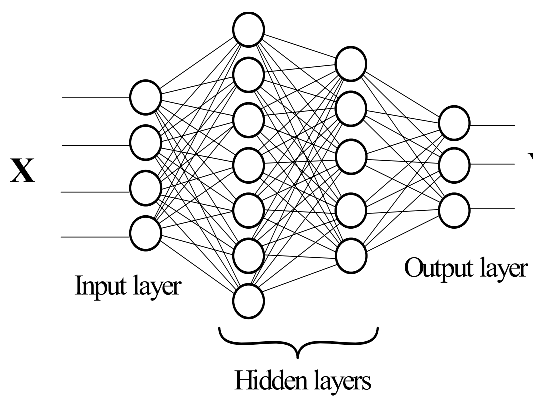

Fig 1. Architecture of a typical artificial neural network

The neural network was trained to solve the classification task by applying resilient backpropagation learning algorithm. The network performance in this study was measured by the modified regularisation error function:

$$E_{MSEREG} = \gamma E_{MSE} + (1-\gamma) E_{MSW} \tag{2}$$

where γ is the performance ratio in a range [0;1]; E_{MSE} – the mean of the sum of squares of the network errors; $E_{MSE} = \frac{1}{n}\sum_{j=1}^{n} w_j^2$ - the mean of the sum of squares of the network weights and thresholds.

During iterative training a *leave-one-out cross-validation* technique was applied. *Cross-validation* refers to the process of assessing the predictive accuracy of a model in a *cross-*

validation sample relative to its predictive accuracy in the *learning samples* from which the model was developed. Each sample is sequentially removed from the training set and the model is trained on the (N-1) remaining samples. The excluded sample becomes the validation set. While the learning set was used to adjust the network weights, the validation sample maintains an independent check that the neural network is learning to generalize (Fig.2)

The interpretation of the network output is based on the Bayesian posterior probability: the construction project cost variation belongs to the class represented by the output layer neuron of the highest output value.

Classification error was calculated by equation:

$$CE_{RMS} = \sqrt{\frac{1}{q}\sum_{p}\left(T_p - P_p\right)^2}\ , \tag{3}$$

where T_p – actual class of project cost variation; P_p– class of project cost variation predicted by neural network; p – construction project index; q – number of examples for testing.

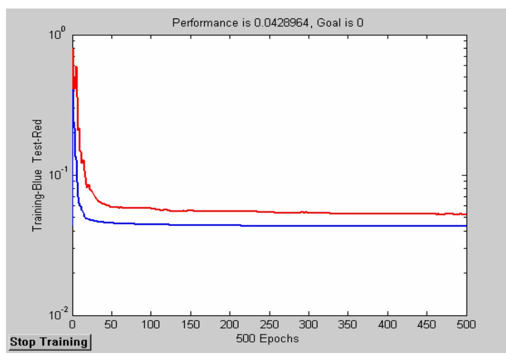

Fig. 2. Neural network error for learning and validation samples

Relative classification error was calculated by equation:

$$CE_{RS} = \frac{q-n}{q}100\%\ , \tag{4}$$

where q- number of examples for testing; n – number of correctly by neural network predicted project cost variation classes for testing samples.

The network's weights and thresholds must be set so as to minimize the prediction error made by the network. Once the number of layers, and number of units in input and output layers has been selected in the beginning, the number of hidden layer units was decided during the network training by calculating the prediction error on the test samples.

All construction management effectiveness factors were incorporated into the model at the first stage of model development. The initial network model comprised 27 neurons in the input layer with 9 neurons in the hidden layer and 5 neurons in the output layer. However, experimentation with an initial model that included all 27 variables resulted in a model with poor performance, thus indicating that including all variables makes the model less sensitive to each of them. In order to understand the importance of a particular input to the network output, a sensitivity analysis technique was applied. A sensitivity analysis technique indicates which input variables are considered most important by the particular neural network. Sensitivity analysis can give important insights into the usefulness of individual variables. It often identifies variables that can be safely ignored in subsequent analyses, and key variables that must always be retained.

2.3 Determination of Key Construction Project Management Effectiveness Factors

Sensitivity analysis was performed by measuring the network output, when each output-input was set (one at a time) to its minimum and then its maximum values. The amount of change in the network output represents the network's sensitivity to a respective input. Thus the priority of the construction management factors to the construction project management effectiveness was evaluated (Table 1). The insignificant factors were trimmed from the network at the stage of model development. This was done gradually by eliminating the least important factors, respectively to the results of sensitivity analysis. During this process 12 key determining construction management effectiveness factors were identified for further model development (Table 3).

Table 3: Key factors of construction management effectiveness

Category	Factors	Influence
Project manager (PM)	PM meetings	Positive
	PM site visits	Positive
	PM subordinates	Negative
	PM education level	Positive
	PM scope experience	Positive
	PM scope experience other than PM	Positive
Project team	Monetary incentives	Positive
Planning	Independent constructability analysis	Negative
	Modularisation	Positive
Organisation and control	Independent control system budget	Negative
	Schedule updates	Positive

Sensitivity analysis confirmed that the initially selected four categories are significant aspects of the cost performance. The selected twelve factors include seven for project manager category, one for project team, two for planning and two for organization and control category. Three key factors, i.e. PM subordinates, independent constructability analysis, and control system budget, showed negative influence on the CPMEM output. These factors appear to be associated with project complexity and risk. The higher project complexity and the higher level of risk degree means the higher values of these three factors: there are more employees and subcontractors supervised by PM, the cost of independent constructability analysis as well as control budget is respectively higher. Nine key factors showed positive influence on the CPMEM output. The higher values of these factors allow improving the construction project management effectiveness.

2.4 Model Validation and Testing

Many experiments with various network architectures were performed during training in order to arrive at the best-trained network. Based on the classification error, the final neural network model was built with 12 neurons in the input layer, 4 neurons in hidden layer and 5 neurons in the output layer (Table 6).

The performance in terms of generalization and prediction qualities of neural network depends significantly on the training data (training patterns) and the domain this data covers. The established CPMEM represents the input-output functional relationships reflected by the specific characteristics of the training data set. Then the model was validated by ten project samples, two for each class. All testing samples were classified correctly. Thus, the results are valid within this particular range of training data. However, the analogical model can be developed by applying training data of any group of construction projects or construction management organizations.

Table 6: Testing results of neural network model

Number of neurons in the layers	Number of iterations	E_{MSEREG}	CE_{RMS}	CE_{RS}
13/8/5	826	0.0304	0	0
13/12/5	951	0.0284	0	0
12/2/5	1251	0.1203	0.89	20
12/3/5	851	0.0965	0.89	20
12/4/5	1151	0.0957	0.45	10
12/4/5	1276	0.0953	0	0
12/4/5	1476	0.0944	0	0
12/6/5	1351	0.0848	0.32	10
12/7/5	851	0.0753	0.32	10
12/9/5	1051	0.0547	0	0
11/5/5	801	0.1364	0.89	20
11/6/5	751	0.1342	0.63	20
11/9/5	1251	0.1333	0.63	20
10/4/5	676	0.2157	1	40

3. Decision–Support Tool for Competitive Bidding

The construction industry has been presented with a number of analytical and numerical models for the calculation of the probability of winning and optimization of bid markups. The traditional bidding models of Friedman (1956) and Gates (1967) are based on the bidding history of a firm’s competitors. Shaffer and Michaeu (1971), Benjamin (1972), Griffis (1992), Ahmad and Minkarah (1998) and Christodoulou (2004) introduced more quantitative and qualitative factors in the development of the expanded mathematical bidding models. However analytical models simplify the problem to one of consisting only two internal project parameters (cost estimate and bid markup) and focusing on the external factors: the level of competition, status of economy, the firm’s need for work, etc.

Authors of the paper established the construction project management effectiveness model and developed the application algorithm of that model for competitive bidding process (Fig.3). CPMEM for competitive bidding process captures all the other objective and subjective internal company's and project factors that govern bid decisions.

The range of potential construction project cost variation can be evaluated by applying CPMEM on the specific project, project team and construction company as follows (Fig 3):

- The first stage's target is to obtain the maximum of existing information about the main features of the project.
- The second stage entails a detail study of the project, suggesting possible changes for the project, estimating costs and defining target bid markup.
- In the third stage the project management team is formed to deal with the project planning, management and delivery. In that stage the intended project management effectiveness factors should be evaluated.
- In the fourth stage the project's construction cost variation is predicted by applying CPMEM. This step is very useful to identify hidden project management risks.
- In the fifth stage the initial total bid price is adjusted according to the CPMEM results.
- The sixth stage entails a search and analysis of historical information about similar internal and external projects. The obtained information about the potential competitors and their strengths and weaknesses should be measured. Then the adjusted bid price should be evaluated in comparison with forecasted prices of competitive bidders.
- Finally, the decision if everything goes forward or if the project requires serious reconsideration should be made. If the project management system considered to be changed, the potential project management factors (e.g. different project planning or control strategy, different project team size or qualification, organizational structure, etc.) should be re-evaluated. The analysers should go back to the third stage and repeat the process until the selected criterion is satisfied. If the project management system considered not to be changed, the decision about the participation in the bidding process should be made.

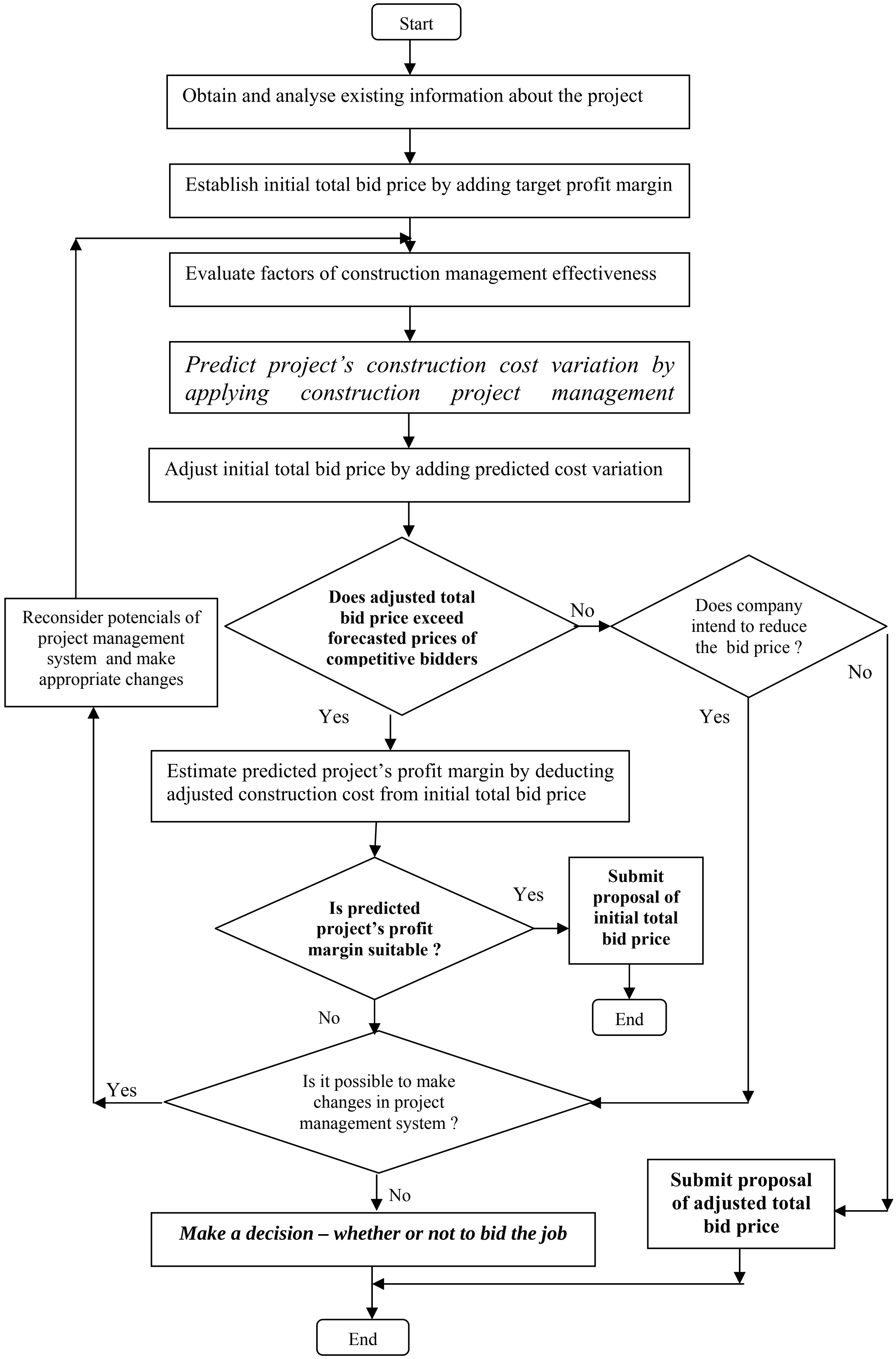

Fig. 3. Construction project management effectiveness prediction algorithm

Case study: The request for bidding proposal was issued by the private company to manage the construction of industrial project of 20 million USD on a fixed price contract basis. Construction company X prepared bidding material for that project. Company's X estimated total bid price was 20.7 million USD, 10 % profit margin was included. According to the market analysis the competitive bids might fall into the range of 20-21 million USD. What would be the company's X bidding decision?

Solution: The estimated construction cost was 18.82 million USD. The predicted cost variation was calculated within the range of –3 % and +3 % by applying CPMEM construction projects management effectiveness neural network model. If the worst happened, the construction cost would increase by 3 % up to 19.38 million USD and the markup would reduce to 6.8%. If the target markup for that project procurement was 10%, the company should re-estimate the bid price up to 21.32 million USD. Though, that price would not be competitive.

The managers decided to replace two members of the project team by more qualified professionals and not to hire outside consultants, i.e. re-evaluated the CPMEM factors of project team monetary incentives and independent constructability analysis. By applying CPMEM model for the second time, the predicted cost variation was calculated within the range of +3% and +10%. In that case there was a possibility of at least 3% construction cost reduction, i.e. 0.56 million USD (18.82*0.03=0.56). Thus, adjusted bid price was calculated at 20.08 million USD [(18.82-0.56)*1.1] =20.08.

X company must make a decision – whether to submit the bid price of 20.08 million USD, which seems competitive enough, or keep trying to reduce it by strengthening the other aspects of project management system, thus resources can be deployed even more effectively.

By applying CPMEM the construction project management effectiveness neural network model, managers of construction company can indicate how much importance each factor has for a particular project outcome, find the best possible arrangement of construction management effectiveness factors and examine the construction cost variation tendencies. Civil engineers and managers are uniquely positioned to take use of the opportunities offered by the new paradigm.

4. Conclusions

The paper presents new methodology for modelling of construction project management effectiveness by applying artificial neural networks. The approach of artificial neural networks allows the construction projects management effectiveness model to be built and to determine the key determinants from a host of possible management factors that affect project effectiveness in terms of construction cost variation.

Survey questionnaire was created and distributed to construction management companies in Lithuania and the US. Collected data of projects' performance has been used to build the neural network model. Twelve key determinants factors that influence project management effectiveness were identified covering areas related to the project manager, project team, project planning, organization and control.

The established neural network model can be used as a decision-support tool for competitive bidding process to evaluate management risk of a construction project and predict construction cost variation. The model allows the construction project managers to focus on the key success factors and reduce the level of construction risk. The model can serve as a framework for further development of construction management decision support systems.

References:

Adeli, H, and Wu, M. (1998). *Regularization neural network for construction cost estimation.* Journal of Construction Engineering and Management, Vol. 124, No.1, pp. 18-24.

Ahmad, I. and Minkahar, I. (1998). *Questionnaire survey on bidding in construction.* Journal of Management in Engineering, Vol. 4, No. 3, pp. 229-243.

Angelides, D.C. (1999). *Project management and good technical and business practices.* Journal of Management in Engineering, Vol. 15, No. 3, pp. 78-87.

Ashley, D.B., Lurie, C. S., and Jaselskis, E. J. (1987). *Determinants of construction project success.* Project Management Journal, Vol. 18, No. 2, pp. 69-79.

Back, W. E. and Moreau, K. A. (2000). *Cost and schedule impacts of information management on EPC process.* Journal of Management in Engineering, Vol. 16, No. 2, pp. 59-70.

Benjamin, N.B.H. (1972). *Competitive bidding: the probability of winning.* Journal of the Construction Division, ASCE, Vol. 98, No. 2. pp. 313-330.

Bower, D., Ashby, G., Gerald, K., and Smyk, W. (2002). *Incentive mechanisms for project success.* Journal of Management in Engineering, Vol. 18, No. 1, pp. 37-43.

Chan, A.P.C., Ho, D.C.K., and Tam, C. M. (2001). *Design and build project success factors: multivariate analysis.* Journal of Construction Engineering and Management, Vol. 127, No. 2, pp. 93-100.

Cheng, E.W.L., Li, H., and Love, P.E.D. (2000). *Establishment of critical success factors for construction partnering*. Journal of Management in Engineering, Vol. 16, No. 2, pp. 84-92.

Chua, D.K.H., Kog, Y.C., Loh, K., and Jaselskis, E.J. (1997). *Model for construction budget performance – neural network approach.* Journal of Construction Engineering and Management, Vol. 123, No. 3, pp. 214-222.

Chua, D.K.H., Kog, Y.C., and Loh, P. K. (1999). *Critical success factors for different project objectives.* Journal of Construction Engineering and Management, Vol. 125, No. 3, pp. 142-150.

Christodoulou, S. (2004). *Optimum bid markup calculation using neurofuzzy systems and multidimensional risk analysis algorithm.* Journal of Computing in Civil Engineering, Vol. 18, No. 4, pp. 322-330.

Faniran, O.O., Oluwoye, J.O., and Lenard, D.J. (1998). *Interactions between construction planning and influence factors.* Journal of Construction Engineering and Management, Vol. 124, No. 4, pp. 245- 256.

Friedman, L.(1956). *A competitive bidding strategy*. Operations Research, Vol.4, pp.104-112.

Ford, D.N. (2002). *Achieving multiple project objectives through contingency management.* Journal of Construction Engineering and Management, Vol. 128, No. 1, pp. 30-39.

Gates, M. (1967). *Bidding strategies and probabilities.* Journal of Construction Division, ASCE, Vol. 96, No. 1. pp. 77-78.

Griffis, F.H. (1992). *Bidding strategy: winning over key competitors.* Journal of Construction Engineering and Management, Vol. 118, No. 1, pp. 151-165.

Haykin, S. (1999). *Neural networks: a comprehensive foundation*, New Jersey, Prentice-Hall.

Jaselskis, E.J., and Ashley, D.B. (1991). *Optimal allocation of project management resources for achieving success.* Journal of Construction Engineering and Management, Vol. 117, No. 2, pp. 321-340.
Jan, J.C., Hung, S.L., Chi, S.Y., and Chern, J.C. (2002). *Neural network forecast model in deep excavation*. Journal of Computing in Civil Engineering, Vol. 16, No. 1, pp. 59-65.
Lim, C.S., and Mohamed, M.Z. (1999). *Criteria of project success: an exploratory re-examination.* International Journal of Project Management, Vol. 17, No. 4, pp. 243-248.
Lu, M., AbouRizk, S. M., and Hermann, U. H. (2000). *Estimating labor productivity using probability inference neural network.* Journal of Computing in Civil Engineering, Vol. 14, No. 4, pp. 241-248.
Millet, R. A. (1999). *Failures: how to avoid them.* Journal of Management in Engineering, Vol. 15, No. 2, pp. 32-36.
Mitropoulos, P., and Tatum, C.B. (2000). *Management-driven information.* Journal of Management in Engineering, Vol. 16, No. 1, pp. 48-58.
Mohsini, R.A., and Davidson, C.H. (1992). *Determinants or performance in the traditional building process.* Construction Management and Economics, Vol. 10, No. 4, pp. 343-359.
Molenaar, K.R., and Songer, A.D. (2001). *Web-based decision support systems: case study in project delivery.* Journal of Computing in Civil Engineering, Vol. 15, No. 4, pp. 259-267.
Pinto, J.K and Slevin, D.P. (1988). *Project success: definition and management techniques.* Project Management Journal, Vol. 19, No.1, pp. 67-72.
Sanvido, V., Grobler, F., Parfitt, K., Guvenis, M., and Coyle, M. (1992). *Critical success factors for construction projects*. Journal of Construction Engineering and Management, Vol. 118, No. 1, pp. 94-111.
Shaffer, L.R., and Michaeu, T.W. (1971). *Bidding with competitive strategy models.* Journal of the Construction Division, American Society of Civil Engineers. Vol. 97, No. 1, pp. 113-139.
Shen, L.Y, Wu, Y.Z. (2005). *Risk concession model for build/operate/transfer contract projects.* Journal of Construction Engineering and Management, Vol.131, No.2, pp. 211-220.
Sinha, S.K., and McKim, R.A. (2000). *Artificial neural network for measuring organizational effectiveness*. Journal of Computing in Civil Engineering, Vol. 14, No.1, pp. 9-14.
Tiong, R.L.K. (1996). *CSFs in competitive tendering and negotiation model for BOT projects*. Journal of Construction Engineering and Management, Vol. 1221, No. 3, pp. 205-211.
Zhang, X. (2005). *Critical success factors for public-private partnerships in infrastructure development.* Journal of Construction Engineering and Management, Vol.131, No.1, pp. 3-14.