5th International/11th Construction Specialty Conference
5e International/11e Conférence spécialisée sur la construction

Vancouver, British Columbia
June 8 to June 10, 2015 / *8 juin au 10 juin 2015*

A NEURAL NETWORK BASED MODEL FOR COST ESTIMATION OF INDUSTRIAL BUILDING AT THE PROJECT'S DEFINITION PHASE

AliReza Shafiee[1], Amin Alvanchi[2,4] and Siamak Biglary[3]
[1] Sharif University of Technology, Iran
[2] Sharif University of Technology, Iran
[3] Sharif University of Technology, Iran
[4] alvanchi@sharif.edu

Abstract: Annually there are many small-scale industry projects implemented in Iran, most of which are financed by local financial institutes. The financing agreements between project owners and financial institutes are usually formed and finalized during the initiation phase and are based on feasibility studies done at the early stages; before project design and construction begin. However, in many cases actual costs of projects exceed the costs estimated in feasibility studies which have been approved by financial institutes. Limited financial resources in the country, from one side, and the lengthy process of increasing the project financing limit, from another side, cause delays in the project completion. In many cases the cost increase and the delay make the entire project unfeasible; projects stop forever; a big waste of money is the result. To respond to this issue and improve accuracy of cost estimation prior to the design and construction phases, in this research we have developed a new cost estimation model based on neural network method. At this stage of the research the model is implemented and tested for the main industrial building, which usually has a portal frame structure. Results indicate a reasonable improvement in accuracy for the estimated costs.

1 INTRODUCTION

Small-scale industry projects constitute a considerable part of industrial construction projects in Iran. Statistics for 2014 show that small industries account for 92% of the industries in the country, and that 40% of the total industrial employment is in small industries. (Fars News Agency 2015). Owners of small-scale industry projects generally own smaller industries and workshops and they are completely familiar with their target market. They feel the need to expand and develop their industries and want to increase their production power. So, they take steps to introduce industry projects, but generally they lack suitable project management knowledge. Funds needed to meet the costs of these projects in the country are provided jointly through project owner investments and financing banks. The initial capital required for carrying out projects is one of main factors contributing to the economic justification of building them. However, in many small-scale industry projects in Iran it is observed that the actual costs exceed the estimated capital. This causes many projects to face problems in providing funds during the construction phase. Moreover, many owners of such projects have limited assets and cannot meet the increased costs. On the other hand, increasing bank loan ceilings requires complicated processes and is time consuming; and, in many cases, banks no longer agree to raise their loan ceilings for the projects since elevated costs pull the projects out of their profitability margins.

Compared to large industries, small-scale industry projects generally include limited production lines; a greater part of construction costs in these industries are related to buildings and civil works required. Studies conducted on 30 industrial projects showed that construction expenditure in industrial projects with costs of less than 20 million dollars (small-scale industry projects) constituted 20% of the total costs, while in industrial projects with costs of over 20 million dollars this figure declined to 12%. Moreover, studies have shown the main industrial building accounts for the main part (58%) of the total buildings and civil works in the projects. Furthermore, most owners of these projects need to make sure banks will finance their projects before they start the design and building phases. Therefore, signing a contract with the bank for financing the project usually takes place before the detailed design and based on the initial feasibility studies. Moreover, it is difficult to estimate accurately the costs of constructing civil engineering facilities just by knowing specifications regarding their initial dimensions, and this will reduce estimation accuracy and lead to errors in cost estimation of these facilities. Study of 30 industry projects mentioned above suggested the mean deviation from the allocated budgets for industrial projects was 16% while this figure rose to 30% for the building and civil work parts. Higher variations in cost estimation of civil works compared to production line in small-scale industries originate from the fact that manufacturers of these production lines are usually specialized and have many past experiences in making specific types of machineries required; they already have design of production line machineries and can provide accurate estimations in the early stages. Therefore, what actually causes costs of small-scale industry projects to deviate from the predicted values is inaccurate cost estimation in buildings construction and civil works which need to be custom designed and built. This is also the case for main industrial buildings in which the costs deviate 28% from the allocated budgets.

Inaccurate cost estimation is accompanied by the possibility of increased construction costs because it will cause delays in paying construction contractors, and it will increase the possibility of contractual disputes. The time-consuming process of bank approval in raising loan ceilings, and the loss of economic feasibility of the projects due to increased costs, cause work stoppages in industrial projects or lead to their annulment and termination, as confirmed by the fact that there are 2900 unfinished small-scale industry projects in the country (ISNA press 2014). The importance of initial estimation and its tangible effect on success or failure of a project to the end led us to develop an estimation model based on neural networks in this research. This model is going to receive preliminary specifications of the project, which are determined in the early stages of the project prior to the project design, as the main input and return relatively accurate cost estimation of the project as its output. Though, because of its significant cost contribution and cost estimation variations, in this part of the research our main focus is on the main industrial buildings. Almost in all small-scale industrial projects we studied, including the above mentioned 30 cases, the main industrial buildings were constructed based on portal frame steel structure. So, the model was specifically developed for steel portal frame buildings. With the cooperation of the specialist group for designing and constructing steel portal frame structures for industrial buildings, we designed and used 324 portal frames with various specifications and dimensions based on geographical and environmental features of Tehran province to develop our model, to increase its accuracy, and to train the developed model. Results of validation of the model by using it in actual small-scale industry projects in Tehran province showed a high accuracy in cost estimation.

2 LITERATURE REVIEW

Ellis and Turner in 1986, and Proctor, Brown, et al. in 1993 showed that cost proposals offered by construction contractors were usually higher than the initial estimates and predictions of employers. In recent years, in an effort to narrow this gap, and with the advances made in information technology, new cost modeling approaches based on preliminary project parameters using computer software have been introduced. In 1996, Fortune and Lee compared the reliability and value of these new methods of modeling with those of the conventional ones and demonstrated the new models were more valuable than the conventional ones. Since then, extensive studies were conducted on cost estimation in the early stages of projects by using the new methods developed by computer software.

In 2006, Lowe et al. used multiple regression methods on 286 datasets collected on construction projects carried out in England to predict costs of building construction. They based their cost estimation model on cost per square meter, cost logarithm, and cost per meter logarithm, and introduced six models by performing the two kinds of forward and backward stepwise regression analysis. Finally, the back propagation algorithm cost model showed the best result with a correlation coefficient of 0.661 and mean absolute percentage error of 19.3 percent. These results were comparable with those of previous studies that reported the mean absolute percentage error of cost estimation using conventional methods was about 25 percent. The data Lowe et al. (2006) used for modeling in 2002 was employed by Emsley et al. to develop a neural network model for estimating the total construction cost. Comparing the results of these two studies showed that the performance of the neural network model was a little better than that of the regression model. Sonmez (2004) also studied the use of regression methods and neural networks in conceptual cost estimation models (predesign cost estimation models) in construction projects. He used 30 datasets related to costs of building projects (houses, treatment centers, and public buildings) belonging to the Social Security Administration in 14 different states of the United States built during 1975-1995, and employed the range estimation method to determine cost ranges. The regression model and the neural network models were compared with respect to goodness of fit and prediction performance using the two criteria of mean square error and mean absolute percentage error. Results indicated the neural network models fit the data better.

Superiority of the artificial neural network method in estimating construction costs in the early stages of projects, and comparison of its results with those of other methods, have been the subject of many other studies as well. For example, Garza and Rouhana in 1995, Bode in 2000, Park et al. in 2002, Gunaydin and Dogan in 2004, Kim et al. in 2007 , Arafa and Alqedra in 2011, Petroutsatou et al in 2012, and Kim et al in 2013 conducted similar studies in this regard. In most of these studies, the researchers concluded that artificial neural networks were more useful for cost estimation in the early stages of construction projects and yielded better results. Under conditions of great uncertainty, back propagation neural networks are more suitable for estimating the cost of the finished product, and are a useful tool for cost estimation and for dealing with nonlinear questions. These models do not have the limitations of regression analysis models such as assuming a specific type of equation (e.g., polynomial) for project costs and its related variables, or the limitations of the conventional cost breakdown methods such as the need for accurate costs and detailed quantity information. Of course, one of the challenges faced in using neural networks is that a relatively large number of samples are required for training the model and for testing its efficiency and accuracy.

Although many studies have been conducted on estimating construction costs in the predesign stage, estimation of the initial costs of production buildings in industrial projects has not received much attention. Production buildings have different structures, construction methods, applications, parameters influencing costs, and manner of calculating costs from residential buildings which have mainly been address in previous estimation models. Therefore, this research studied the development of a new model based on using neural networks to meet the need for cost estimation and calculation related for portal frame industrial buildings in the predesign stage.

3 THE COST ESTIMATION MODEL

The cost of steel structure of industrial buildings depends on various factors such as the required workforce, price of steel in the market, transportation cost, etc. One of the main factors influencing costs of steel structures is the weight of steel used or more commonly called the steel structure weight. Therefore, an accurate estimate of the weight of steel to be used must be made before estimating costs. That is why this study was divided into two main phases. In the first phase, a model was built for estimation of the portal frame steel structure weight based on initial specifications. The output of this model, and other parameters influencing costs of steel structures, were then used in the second phase as the input of the second model to estimate construction cost of the steel structure so that a suitable estimate can be made of the costs of the main production building or the steel structure. Figure 1 shows the conceptual cost estimation and calculation model for the production building. The part marked by dotted lines represents the first modeling phase (which is the subject of this article).

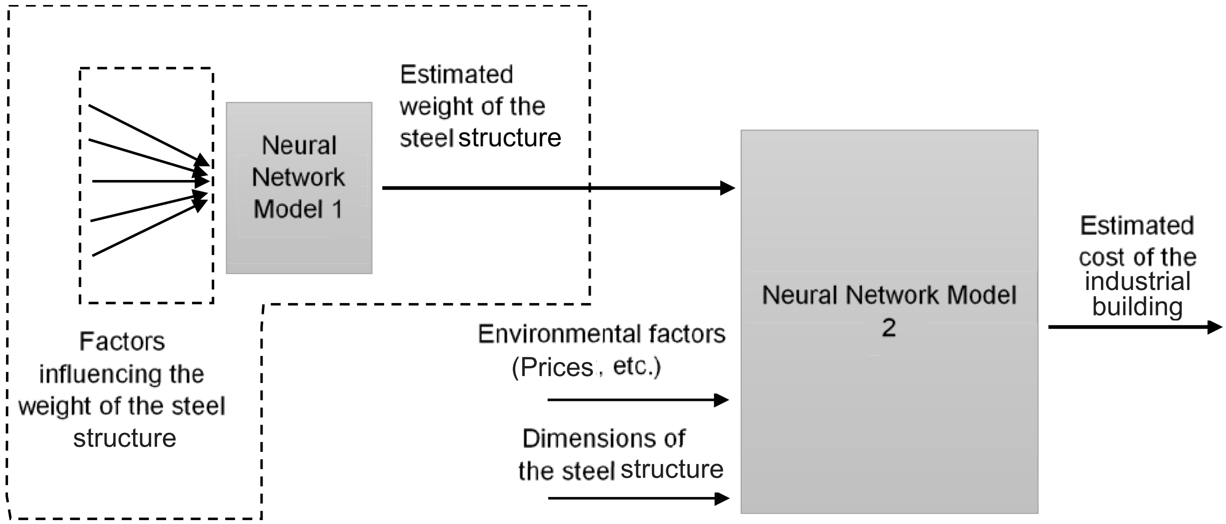

Figure 1: The conceptual cost estimation and calculation model for steel structure

3.1 Factors influencing the weight of portal frame steel structure

Portal frame indusial buildings are mostly one-floor structures with pitched roofs and vertical members (e.g., columns), sloping member (e.g., rafter), and diagonal members (e.g., wind braces) which are used to cover large spaces. One of the most important criteria determining the cost of a portal frame steel structure is the weight of the steel used, which itself is a function of various geometric and non-geometric specifications of the project. That is why sessions were held with experts in the design and construction of steel structures to ask their views on factors influencing the weights of steel structures. A joint research group including experts, designers, and builders of portal frame steel structures was formed to identify and evaluate importance of factors affecting the weight of portal frame in industrial buildings. These factors and their effects on the steel structure are briefly described below.

1. Building width: Increase of the building width or building span increases the length of rafters. Therefore, the bending moment resulting from the dead weight of the roof, snow and wind loads is also increased, which will naturally increase the weight of the structure.

2. Height of the hall (from the ground to the apex): With increases in the height of the steel structure, the effects of wind load on the columns and on the rafters will be intensified, and these effects in the moment diagrams of the rafters and the columns will include changes in the second degree. Another important factor in this case is the increase in the tenderness ratio and, consequently, the decrease in permissible compressive stress. These factors together necessitate the use of heavier sections.

3. Hall length: increases in the length of the steel structure will increase its weight, which in fact is the deciding factor in determining how much force an earthquake impacts on the steel structure. This will even more increase the weight of the steel structure.

4. Snow load of the region.

5. Other loads such as the crane, the indoor floors, the false ceiling.

6. The number of spans or the sharing of the base with side steel structures: although increases in the number of spans raise the reliability coefficient of the structure against collapse resulting from wind and earthquakes, the added members increase the weight of the steel structure.

Therefore, the input parameters of the model were selected from these factors to build the neural network model. The reason was that they are not only the most important factors influencing the weight, and hence the cost of the steel structure, but are also among the preliminary specifications of the main industrial building that are determined before the design process in the early stages of project definition.

3.2 Designing various types of portal frame steel structure

Results of research conducted by Gunaydin and Dogan in 2004 showed that the performance of the artificial neural networks in cost estimation strongly depended on the quality and quantity of the samples because neural networks are trained by data related to samples. Prediction error decreases with increases in the number of samples. Therefore, reliable, high quality, and full-scale data concerning costs of various types of buildings under different conditions is required to study modeling methods and to predict and build an accurate cost estimation model. To obtain such data, it was decided to ask the expert design team to design the required samples needed for building the neural network model by changing factors that influence the weight of a portal frame steel structure. In changing these effective factors, it was taken into account that the samples used to train the neural network had to be able to cover the range of values related to steel structure specifications that may actually be used in designs related to small-scale industry projects. Therefore, small-scale industry projects were studied and the opinions of the builders and designers of structures used in these projects were asked to identify the range of changes in factors that influence the weight of the steel structures, and to use this range in selecting samples that formed the input of the neural network. In all, the design specialist team identified 324 steel structures through changing the factors that influence the weight of a steel structure so that we could conduct our research.

The types of loading structures vary in different regions of the country, and so do the snow, wind, and earthquake loads. Therefore, in this stage of the research, structure designs in Tehran Province were studied. The same dead load, live load, and earthquake load were considered for all models, and the geometric specifications of the structures and the snow and wind loads in Tehran were taken into account in considering the base snow, wind, and crane loads. Furthermore, the maximum difference in stress ratios of the main members similar in the structures of various models was considered 10% in order to extract output results with suitable accuracy. Moreover, the standard stress ratio of the main members of the structures was considered 0.9%; and, considering this ratio, we can say that the design process was carried out optimally. The steel materials commonly used in building steel structures in the country are of the ST-37 and ST-52 types. However, taking into account the industrial structures commonly built, considering the consultations we had with design consultants, and as the needed samples were to be used in small industries, the ST-37 type was selected in designing the samples. Furthermore, given the variety in soil resistance in different places, and considering Tehran is located on the southern slopes of the Alborz mountain range, it was deemed suitable to consider soil type to be grade 2 in calculating earthquake coefficient.

Study of changes in the dimensions of the spans in steel structures without ceiling cranes showed that snow load (as expected) was the dominant load combination in large-span structures because of the large area of the ceiling. However, in small- and medium-size structures the snow and the wind loads were of equal importance in the dominant load combination. Changes in the overall length of the structures did not change the dominant load and section specifications. Changes made in the height of the crown also yielded the expected results, and it was found that wind load was the dominant load in structures with great heights because of the large area of the structure, while the snow load was the dominant load in structures with medium and low heights. Changes in the number of spans indicated that the load combination consisting of the snow load and the earthquake load was the dominant load in the middle columns of these structures, while the load combination including the snow load and the dead load was the deciding load in the lateral columns.

All built models were then studied with the presence of ceiling cranes having 10, 20, and 30- ton capacities under the previous modeling conditions. After examining the output of the V16SAP2000 software, it was found that in all of the built models, except for structures with great heights, the load combination consisting of the crane load and the snow load, and the load combination consisting of the dead weight and the snow load, were the deciding load combinations to similar degrees. In structures with great heights, the load combination consisting of the wind load and the snow load was the only critical load combination. Study and comparison of the models showed the minimum changes in the weight of the structures resulting from increases in the weight of the cranes were those of the structures with great heights because the wind load became the dominant load when the weight of the cranes was added. Moreover, weight changes were not significant in structures with large spans compared to other geometric changes because the snow load was the dominant load. It is worth mentioning that when a crane is added to the structure, the weight of the crane supporting beams must also be included in the weight of the structures and be taken into account in calculations regarding the weight of structures that have cranes.

3.3 Training the neural network of project cost estimation model

In building the neural network model, the data designed in the previous section was used. Creation of network architecture requires the determination of its various components such as the number of intermediate layers, the number of neurons in each layer, and the activation function. This proposed model has five processing elements (neurons) in the input layer and one processing element (neuron) in the output layer. The trial and error method was used in developing the intermediate component of the neural network to obtain a network with the best performance. In the end, the intermediate component with one layer and six processing elements (neurons) was selected for the model because its performance was more desirable compared to other networks.

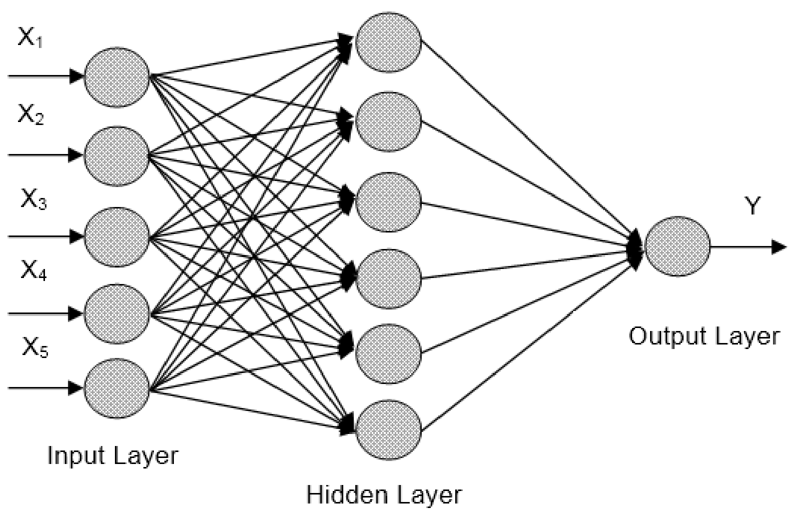

Figure 2: The architecture of a neural network model

Table 1 lists the input parameters of the network. These are the same parameters that influence the weight of the pitched roof portal frame and were introduced in section 3.1. Their specifications are presented in Table 1. Considering the explanations offered in section 3.2, and since the proposed model is for Tehran Province, soil type and geographical characteristics are considered constant in this stage and are not included among the model inputs.

Table 1: Parameters used in designing the model

Design parameter (1)	Definition (2)	Range (3)
X1	Width	6-30 m
X2	Length of the hall	18-72 m
X3	Height	6-24 m
X4	Number of bays	1-5 m
X5	Crane load	Without crane (0), 10-ton crane (1), 20-ton crane (2), 30-ton crane (3)

Three hundred and twenty four designed samples were used to train the neural network. The data was divided at random into three groups. The first group with 70% of the data (the equivalent of 227 data items) for training the neural network, the second group with 10% of the data (or 32 data items) for validation, and the third group with 20% of the data (the equivalent of 65 data items) for examining model efficiency and for testing the model. All the stages of building, training, and testing the model were carried out by using Matlab R2014b. The activation function determines network behavior and is of great importance. After comparing the efficiencies of the various functions, the hyperbolic tangent sigmoid function was used for the intermediate layer (equation 1), and the linear activation model was used for the output layer.

[1] Hyperbolic tangent sigmoid (x) = $\frac{1-e^{-2x}}{1+e^{-2x}}$

One of the important points in creating a neural network model is the determination of the algorithm for training the network. Various algorithms have been developed and introduced so far for training neural networks. Based on a study conducted by Rumelhart (1986) et al., the back propagation algorithm, which follows supervised teaching practice, is very efficient for building nonlinear models and is widely used. We also used this method for training the neural network in our research. Accordingly, the method is used in the current research for training Neural Network is forward training of Neural Network relied on Marquardt algorithm and employed the function of minimum squared error (MSE) for correcting weights during the training of the network (Hagan et al. 1994). The network was thus trained and a trained model with R = 0.9974 was obtained for the training data. After training the model with the 227 samples, its efficiency was evaluated using testing data. In this stage, the weights of steel used in 65 samples were first estimated by employing the neural network model, and the calculated weights were then compared with the actual ones (obtained from detailed design). Figure 3 shows results of the comparison.

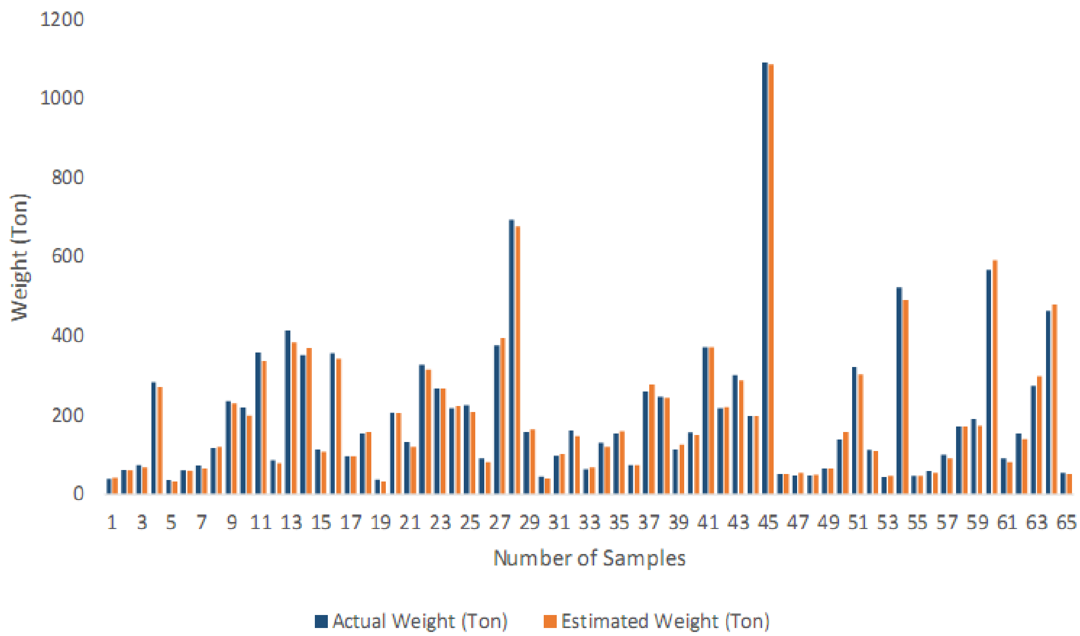

Figure 3: Comparison of the actual values with those estimated by the neural network model for testing data

The percentage relative error was used to evaluate the accuracy of the model in estimating the data. The percentage relative error of the testing data was calculated using equation 2. Study of the accuracy of the estimates made by the model in the testing data showed that the proposed model had a suitable performance with 95% accuracy and could well be used in the early and pre-design stages in small industrial projects.

$$\text{Percentage Error} = \frac{\text{Estimated Weight (i)} - \text{Actual Wight (i)}}{\text{Actual Weight (i)}} \times 100\%$$

4 CONCLUSION

In this research, a model based on neural networks was developed for estimating cost of main industrial buildings for small industry projects in the pre-design stage. In the first part of the research a model was developed for estimating the weight of steel used in portal frame industrial building. Coordination was made with the professional group that designed the portal frame and 324 portal frame steel structures were designed by changing values of factors influencing the weight of these frames to increase the accuracy of the calculations. The neural network model was then trained and evaluated using the above-mentioned data and, finally, a model was obtained with the accuracy of 95%. The weight and cost estimation model of the portal frames developed is based on preliminary dimensional characteristics of the structure which helps consultant engineering companies to increase accuracy of their estimates in their feasibility studies. It also enables them to better evaluate the prices offered by contractors. More accurate estimations during initial phase also accelerate the preparation of bidding documents, increase reliability of prices offered, and decrease the probability of deviating from the allocated budgets with the consequent fines falling behind schedule or for delays in the project due to insufficient budget. Moreover, financing banks will be able to use similar models and software to increase their accuracy and reduce their risks. Although the introduced model was developed based on geographical specification of Tehran, it can be easily expanded to other regions by proving the geographical specification of the desire location as inputs to the model. Results obtained from the model will be presented to those active in small-scale industries including owners of projects, banks, consultant engineers, and builders to make more improve their projects construction phase.

References

Ellis C. and Turner A. 1986. Procurement problems. *Chartered quantity surveyor*, April, p.11

Proctor C.J., Bowen P.A., Le Roux G.K. and Fielding M.J. 1993. Client and architect satisfaction with building price advice: An empirical study, *CIB W55/W95 International symposium on economic evaluation and the built environment*, Lisbon, 213-226.

Fortune, C.J., and Lees, M.A. 1996. The Relative Performance of New and Traditional Cost Models in Strategic Advice for Clients, *RICS Research Paper Series,* **2**(2)

Arafa, M., and Alqedra, M. 2011. Early Stage Cost Estimation of Buildings Construction Projects Using Artificial Neural Networks, *Journal of Artificial Intelligence,* **4**(1): 63-75.

Bode, J. 2000. Neural Networks for Cost Estimating: Simulation and Pilot Application. International Journal of Production *Research*, **38**(6): 123-154.

Emsley, M. W., Lowe, D. J., Roy, D. A., Harding, A. and Hickson, A. 2002. Data Modeling and the Application of A Neural Network Approach to the Prediction of Total Construction Cost. *Construction Management and Economics*, **20**(6): 465–472.

Fars News Agency. 2015. Small industries contribute to 43 percent of the countries employment. *http://www.farsnews.com/newstext.php?nn=13931130000696*. Feb 19, 2015. accessed on Feb 19, 2015

Garza, J. and Rouhana, K. 1995. Neural Networks versus Parameter-Based Applications in Cost Estimating. *Cost Engineering*, **37**(2): 14-18.

Gunaydin, H. and Dogan, S. 2004. A Neural Network Approach for Early Cost Estimation of Structural Systems of Building. *International Journal of Project Management*, **22**(7): 595-602.

Hagan, M. T. and Menhaj, M. 1994. Training Feedforward Networks with the Marquardt Algorithm. *IEEE Transactions on Neural Networks*, **5**(6): 989- 993.

ISNA press. 2014. Government speaker: There are more than 2900 incomplete projects in the country. *http://www.isna.ir/fa/news/93073017591*. Oct 22, 2014. accessed on January 31, 2015

Kim, G.H. and An, S.H. 2007. A Study on the Correlation between Selection Methods of Input Variables and Number of Data in Estimating Accuracy; Cost Estimating Using Neural Networks in Apartment Housing Projects. *Journal of the Architectural Institute of Korea*, **23**(4): 129-137.

Kim, G.H., An, S.H. and Cho, H.K. 2006. Comparison of the Accuracy between Cost Prediction Models Based on Neural Network and Genetic Algorithm: Focused on Apartment Housing Project Cost. *Journal of the Architectural Institute of Korea*, **23**(3): 111-118.

Kim, G.H., Shin, J.M., Kim, S., and Shin, Y. 2013. Comparison of School Building Construction Costs Estimation Methods Using Regression Analysis, Neural Network, and Support Vector Machine. *Journal of Building Construction and Planning Research,* **1**(1):1-7.

Lowe, D. J., Emsley, M. W. and Harding, A. 2006. Predicting Construction Cost Using Multiple Regression Techniques. *Journal of Construction Engineering and Management*, **132**(7): 750–758.

Petroutsatou, K., Georgopoulos, E., Lambropoulos, S., and Pantouvakis, J. 2012. Early Cost Estimating of Road Tunnel Construction Using Neural Networks. *Journal of Construction Engineering and Management,* **138**(6): 679-687

Rumelhart, D.E., Hinton, G.E. and Williams, J.R. 1986. Learning Representations by Backpropagation Errors. *Nature*, **323**: 533-536.

Seo, K.K., Park, J.H., Jang, D.S. and Wallace, D. 2002. Approximate Estimation of the Product Life cycle Cost Using Artificial Neural Networks in Conceptual Design. *International Journal of Advanced Manufacturing Technology*, **19**(6): 461-471.

Sonmez, R. 2004. Conceptual Cost Estimation of Building Projects with Regression Analysis and Neural Networks. *Canadian Journal of Civil Engineering*, **31**(4): 677-683.