Analysis of Cost and Schedule Variances in Construction Works with Artificial Intelligence Approaches: The Case of Turkey

Savaş Bayram[1], Mehmet Emin Öcal[2], Emel Laptalı Oral[3]

[1]*Department of Civil Engineering, Erciyes University, Kayseri, Turkey*
[2, 3]*Department of Civil Engineering, Cukurova University, Adana, Turkey*

ABSTRACT

Realistic estimation of construction cost is a vital issue for both successful planning and completion of every construction project. However, fluctuations in input prices due to the unexpected changes in factors like inflation and supply/demand balance make realistic cost estimation very difficult to achieve. Thus, various estimation methods have been developed and these can be grouped as methods based on; statistics-probability analysis, comparison with similar projects and artificial intelligence techniques.

Statistics-probability analysis is the most widely used method for construction cost estimation in Turkey. Based on the so called method, Ministry of the Environment and Urbanism publishes and updates "Unit Costs of Construction" every year and the data is widely used for preliminary cost estimation by both the contractors and the developers. Meanwhile, methods based on artificial intelligence techniques are rarely used within the industry. Thus, the aim of this study has been to compare the estimation results obtained by using statistics-probability analysis and artificial intelligent techniques. In order to achieve this, construction cost data from 198 projects; completed between 2004-2010 in Izmir (the third largest city in Turkey) were used. Multi layer perceptron (MLP) and grid partitioning algorithm (GPA) were used to obtain estimation results and root mean square error (RMSE) and coefficient of determination (R^2) were calculated for comparisons.

Keywords: *Project preliminary cost, project schedule, cost variance, multi layer perceptron, grid partitioning algorithm.*

INTRODUCTION

In the construction sector, which is an important force for the economies of countries, large variety and amount of supply that is used in the production makes it difficult to complete the projects conducted in the sector as originally intended. Thus, it is inevitable to make effective applications in such fields as planning, programming, and cost estimate/analysis even to implement a simple production [1].

To establish a correct financial model even during pre-design stage of construction is very crucial to avoid waste of natural resources [2,3] and this is only possible through a correct cost estimation [2,4]. Cost estimation of a construction may be defined as the short term estimation of the actual costs of a construction under certain conditions [3,4].

In Turkey, cost estimation during pre-design stage is obtained usually by multiplying the total construction area of a building by the construction cost of the unit area and the construction cost of a unit area for a building, "the Notice Concerning the Approximate Construction Unit Costs to Be Used While Calculating the Service Charge of Architecture and Engineering" which is updated annually by the Ministry of the Environment and Urbanism is employed. However, by using this method in which only construction area is taken into consideration ("unit cost method"), equal cost values may be obtained for two different constructions with totally distinct designs. However, construction costs depend on a great number of factors such as the time and location of the building, the ground and surrounding conditions and the technology used [2,3]. Thus, it is an essential matter to determine the effective calculation method to be used in order to estimate the costs correctly during pre-design stage [2,5].

In this study, the aim is to identify the accuracy of the results obtained by using unit cost method by comparing the estimate results with the completed project results under the Public Tender Law no 4734, by identifying both the cost variances and schedule variances and to search for the applicability of artificial intelligence in estimating the cost and schedule variances of the projects. Thus, the files of 198 building projects in total were reviewed, which were procured in accordance with the Public Tender Law by the Ministry of Environment and Urbanism and completed between 2004-2010 in Izmir, which is the third largest city of Turkey. From these files, the estimated and actual time and cost values of the projects in question were obtained and schedule and cost variances of each project were calculated.

PREVIOUS STUDIES

Siqueira (1999) developed a cost estimation method based on neural networks in order to estimate the costs of low-rise prefabricate steel buildings. The data used in the study were obtained from 75 different building projects in Canada. The cost model developed was compared with the data obtained from the project. The results showed that the proposed model was superior to regression method provided the model was employed within the instructed range [6].

Kim et al (2004), examined the performances of three different cost estimation models. These models were specified as multiple regression analysis, neural networks and case-based reasoning. 530 different models from the past were analyzed. Consequently, although the neural network model gave more accurate estimation results, case-based reasoning method showed a better performance than the neural network method when the long-term use was taken into consideration [7].

Günaydın and Doğan (2004), aimed to identify the benefits of a neural network model to overcome the cost estimation problems that appears in the early stages of the construction design processes. So, cost and design data were obtained from different projects, and these data were entered to the neural network and tested. 8 parameters were used and unit costs of 4-8 storey residential buildings in Turkey were calculated. The accuracy of cost estimation was by 93% [8].

Turhan (2006) examined the tender files of 1313 building projects in total which were made by The Public Works and Settlement directorates in accordance with the laws with the numbers 2886 and 4734 and finalized. As a result, it was found that the building projects conducted under the law no 2886 were completed with a cost which was 218,97% higher than the expected cost. On the contrary, the building projects conducted under the law no 4737 were found to be completed with only a 0.89 % variance [9].

Uğur (2007) estimated the construction costs of the multi-storey reinforced concrete buildings with similar qualifications by using unit cost method. Additionally, he included the neural network applications. The main evaluation criteria for artificial neural network architecture were considered to be the height of the building, the number of the flats in a typical floor, typical floor area, heights of each floor, the total number of the floors, facade area, facade space area and mean flat area as calculated from the projects. Cost estimation was undertaken through regression analysis and the performance of the neural network method was analyzed by comparing the results from these three methods [3].

As a summary, the results from the literature search show that artificial intelligence methods also have a usage area besides the traditional methods for time and cost estimation and positive results are obtained from these methods. However, the fact that the main focus of the previous studies being the cost and schedule variances rather than the realistic cost and time estimation sets the difference of this study from the others.

METHOD

The aim of the current study has been to compare the estimation results obtained by using statistics-probability analysis and artificial neural network models. Thus, the “Unit Cost Method” which is based on statistics-probability analysis was firstly used. The total construction area values obtained from the archive studies were multiplied by the unit prices set in accordance with “The notice concerning the approximate construction unit costs to be used while calculating the service charge of architecture and engineering”.

An artificial neural network (ANN) model was then used in order to estimate the project costs. In general terms, ANN may be defined as a system to model the method conducted by the brain to perform a task [3]. ANN uses the examples to identify the relations between the events and benefits from the learned relations as a tool to interpret the problems encountered in the future and to make a decision. Moreover, the ability of the ANN to obtain the concepts from previous data without requiring any mathematical formulation or algorithm is an advantage over other methods [10,11]. Multilayer perceptron (MLP) is a widely used form of ANN approaches as a number of learning algorithms use this network to instruct. As for the grid partitioning algorithm (GPA), it is an artificial intelligence approach which uses adaptive network based fuzzy inference system (ANFIS) which is one of the artificial intelligence algorithms in which hybrid learning algorithm is used and which includes the advantages of learning power of the ANN approach and rule based inference mechanisms of the FL approach [10,12]. In literature, there are findings stating that the estimate capability of the ANFIS approach is better than ANN approach because it involves improved data analysis methods such as numerical classification and establishing rules [10]. The main and the most powerful aspect of ANFIS architecture is its ability to define nonlinear complicated systems through its adaptive auditory structure [10]. Therefore, in this study GPA approach is also dealt in addition to MLP. In GPA modeling, the number of fuzzy rules are set exponentially according to the number of entrance and membership functions and this structure is not preferred when the number of the parameter inputs is more than six [12]. In GPA, back propagation and hybrid learning algorithms may be used to create a model and optimize it. In other words, fault propagation in instructing may exist in two forms as back propagation and hybrid. As the hybrid method is a faster method than the back propagation method, hybrid is used as the optimization method in this study.

APPLICATION

In the archive study carried out in Izmir Environment and Urbanism Provincial Directorate, tender files of 198 completed construction works were analyzed. The distributions of the analyzed files according to the years are given in Figure 1. The distribution of the completed buildings according to their usage purposes can also be seen in Figure 2.

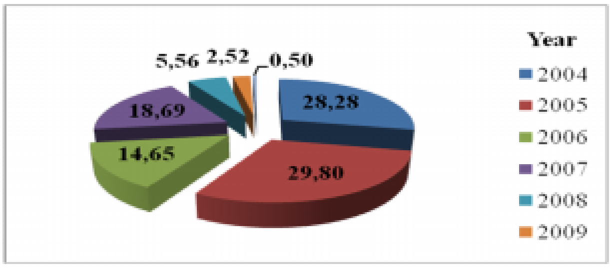


Figure 1 Distribution of the analyzed files according to years

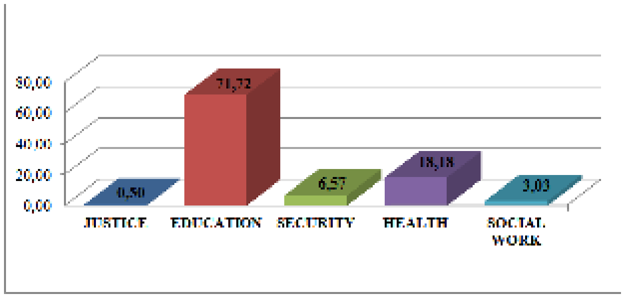


Figure 2 Distribution of the completed buildings according to usage purpose

Among the analyzed tender files, the greatest number of construction according to their year is seen in 2005 with 59 buildings. It is also observed from Figure 2 that the purpose for the 142 of the buildings is education (school, kindergarten, dormitory etc).

Table 1 gives unit costs of construction between 2003 and 2010, categorized according to the classes of the buildings based on the buildings' architecture services.

Table 1 Unit Area Costs From Year 2003 to 2010 (Turkish Lira)

BUILDING CLASS	YEAR							
	2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
I.A	43,00	46,00	51,00	54,00	61,00	65,00	71,00	73,00
I.B	75,00	80,00	89,00	94,00	105,00	112,00	123,00	127,00
II.A	118,00	127,00	141,00	149,00	167,00	178,00	195,00	201,00
II.B	161,00	173,00	193,00	205,00	230,00	245,00	268,00	276,00
III.A	264,00	283,00	315,00	334,00	375,00	399,00	437,00	448,00
III.B	300,00	322,00	359,00	381,00	427,00	455,00	498,00	511,00
IV.A	339,00	364,00	406,00	430,00	482,00	513,00	561,00	577,00
IV.B	375,00	402,00	448,00	475,00	533,00	568,00	622,00	640,00
IV.C	450,00	483,00	539,00	571,00	640,00	682,00	746,00	761,00
V.A	558,00	599,00	668,00	708,00	794,00	846,00	926,00	945,00
V.B	676,00	725,00	809,00	858,00	962,00	1.025,00	1.122,00	1.144,00
V.C	772,00	828,00	924,00	979,00	1.098,00	1.169,00	1.279,00	1.279,00
V.D	922,00	989,00	1.103,00	1.169,00	1.311,00	1.396,00	1.528,00	1.559,00

The areas of the 188 buildings obtained through archive studies were multiplied by the unit costs (where the related buildings ranged from III.A to V.C) and the approximate cost for each structure was obtained. The approximate costs included the general expenditures for the construction and the profit of the contractor. Furthermore, costs of the buildings had construction duration over a year were calculated according to the unit costs in the year before completion. For instance, for a construction which started to be built in 2004 and completed in 2005, the unit costs for 2004 were taken into consideration. Similarly, for a construction which started to be built in 2008 and completed in 2010, the unit costs for 2009 were taken into consideration. The results are given in the "findings and discussion" part.

In this study, two different artificial intelligence models were established for the completed buildings in Izmir between 2004-2010. The input and output parameters for the models are given in Table 2.

Table 2 Input and Output Parameters of the Artificial Intelligence Models

Model Nr.	1. Input	2. Input	3. Input	4. Input	Output
1	Total Construction Area (m^2)	Approximate Cost (TL)	Contract Value (TL)	Cost Variance with Respect Approximate Cost (TL)	Cost Variance with Respect Approximate Cost (%)
2	Total Construction Area (m^2)	Foreseen Project Duration (Day)	-	-	Schedule Variance with Respect Foreseen Project Duration (%)

For the first model, 62 (75%) of the total 82 data were used for the instruction stage while the remaining 20 data (25%) were put aside to be used in the testing stage. For the second model, 141 (75%) of the total 188 data were used for the instruction stage while the remaining 47 data (25%) were used for the testing stage. Four different combinations were created for the Model 1 while two different ones were created for the Model 2 and the combinations were trained through MLP and GPA methods and the learning performances of the networks were tested according to the results. As "Root mean square error" (RMSE) and coefficient of determination (R^2) were considered in order to compare the actual and estimated results. RMSE being close to zero shows the model's increasing ability to estimate [13]. RMSE is calculated through the Formula (1), where; the $Y_{model,i}$ and $Y_{real,i}$ show respectively the model estimations and actual values and n shows the number of data, [14];

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{model,i} - y_{real,i})^2}{n}} \qquad (1)$$

R^2 can be referred as the square of the correlation coefficient and takes a value between 0 and 1. For instance, the connotation R^2=1 means that the dependence between the actual values and the model estimations are quite strong. R^2 is calculated through the Formula (2);

$$R^2 = \frac{\Sigma(x_1 . x_2)^2}{\Sigma(x_1)^2 . \Sigma(x_2)^2}, \quad 0 \le R^2 \le 1 \qquad (2)$$

MATLAB 7.1 simulation software was employed for modeling requirements [15]. In modeling with MLP, the lowest RMSE and the highest R^2 values were sought to be obtained by changing the numbers of the hidden layer and the numbers of iteration for the combinations of both models. The analysis began with the lowest number of hidden layer and iterations. First, the changes in RMSE and R^2 were observed when the iteration number was increased by 10-100 ranges. Then, the numbers of the hidden layer were changed by 5-20 ranges and the effect of the change on RMSE and R^2 was observed. The goal for all combinations was 10^{-5}. In all combinations, Levenberg-Marquard (trainlm) back propagation algorithm was employed as the training algorithm and the logarithmic sigmoid (logsig) was used as the activation function in the hidden layer and output layer. The results obtained are given in the "findings and discussion" part.

In modeling with GPA, the number of membership functions, input membership function type, output membership function type and iteration number were considered as the variables in the combination of both models and the lowest RMSE and the highest R^2 values were sought to be obtained. For each combination, all the variations were tested by the number of membership function by 2 or 3, input membership function Gaussian or triangular, output membership function linear or constant, iteration number increasing by 20 and 100 value ranges by 20, excluding the 5 value. In all combinations, the goal was 0 and the stepsize was 0,02. The results are given in “findings and discussions” part.

FINDINGS AND DISCUSSIONS

The correlation between the approximate costs of 188 building obtained by unit cost method and the actual costs is given in Figure 3. Figure 4 additionally shows the correlation between the approximate cost values of 82 buildings of which the approximate cost values were obtained through archive studies and their approximate costs obtained through unit cost method.

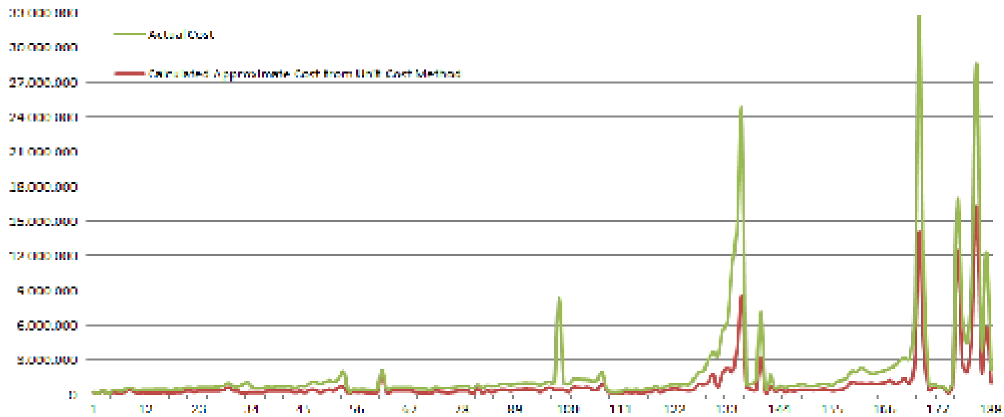


Figure 3 Correlation between the approximate costs obtained by unit cost method and the actual costs

Figure 4 indicates that nearly all the actual costs are higher than the approximate costs obtained through the unit cost method. The sum of the total actual costs of the 188 buildings calculated and the total cost of the approximate costs obtained through unit cost method are given in Table 3.

Table 3 Sum of the Total Approximate Costs Obtained By Unit Cost Method and the Total Actual Costs

Total Work Nr.	Unit Cost Method (U)	Actual Cost (F)	(F-U)	(F-U)/F (%)
188	154.274.203	221.589.212	67.315.009	30,38

As can be seen in the table, the total approximate costs obtained through unit cost method are calculated lower than the actual costs with a variation of 30%.

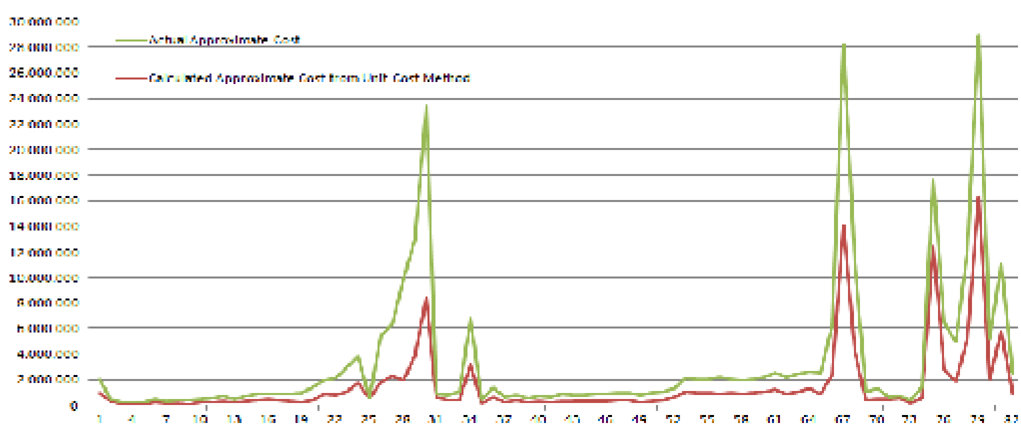


Figure 4 Correlation between the approximate costs obtained by unit cost method and the actual approximate costs

In figure 4, it is seen that the majority of the approximate costs are higher than the approximate costs obtained through unit cost method. However, for about 13 data between data 2 and 10 and data 70 and 73, it can be said that realistic cost estimation is made with the unit cost method. The approximate total costs of the 82 buildings included in the calculations and their estimated total costs obtained through unit costs method are given in Table 4.

Table 4 Sum of the Total Approximate Costs Obtained By Unit Cost Method and the Total Approximate Costs

Total Work Nr.	**Unit Cost Method (U)**	**Approximate Cost (A)**	**(A-U)**	**(A-U)/A (%)**
82	124.308.352	153.846.160	29.537.808	19,20

Total approximate costs obtained through unit cost method are found to be lower than the total approximate costs with a 19% variance. Although this rate of variance by 19% shows that the unit cost method is closer to the approximate cost values than the actual costs, the related variance rate can be said to be far from estimating the accurate costs.

For the MLP method, which is the first artificial intelligence approach used in the study, 64 variations for the Model 1 and 40 variations for the Model 2 were tried in the value ranges stated in the previous part and the optimum RMSE and R^2 values obtained during the test stage of each combination are given in Table 5.

Table 5 Test Results of Models by MLP Method

Model Nr.	**Combination Nr.**	**Number of Nodes in Hidden Layer**	**Iteration Number**	**RMSE**	**R^2**
1	1	5	10	10,7281	0,1642
	2	5	20	6,3933	0,0039
	3	5	30	4,4587	0,4438
	4	10	70	**2,6476**	0,8350
2	1	5	10	81,9228	6,95e-033
	2	10	100	**9,0148**	0,0460

When the RMSE values obtained from the first model is analyzed, it is seen that as the number of the inputs in the combinations increased, the RMSE value decreased accordingly. In other words, each input of the modeling increased the performance of the modeling and as a result, from the combination 4 which consisted of four inputs as total construction area, approximate cost, contract price, and cost variation according to the approximate costs, with 10 hidden layers and 70 iterations, RMSE value was obtained 2,6476 close to the zero value. When the R^2 value is analyzed, it can be said that the fact that the approximate cost values as the second input decreased the rate of accurateness of the modeling is the reason for the lower values of the R^2 values of the second combination than the R^2 values of the first combination. The optimum R^2 value is obtained to be 0,8350 for the combination 4 and this value expresses the numerical relation between the cost variation (%) values obtained from the modeling and actual cost variation (%) values is at 83,50%. In other words, cost variations (%) is estimated through the MLP model by an accurateness of 83,50%. When it is considered that there is a strong correlation between the observed and estimated values when R^2>0,80, it is seen that the result R^2=0,8350>0,80 in the proposed model was at an acceptable level [12]. The findings indicate that MLP modeling was successful in estimating the cost variance (%) for the Model 1. When the RMSE values obtained from the second model are analyzed, the project schedule value projected to be the second input increased the performance of the modeling by 9 fold compared to the total construction area values as the first input. As a consequence, from the combination 2 that consisted of two inputs, with 10 hidden layers and 100 iterations, the optimum RMSE value is found to be 9,0148. However, it is not possible to say that this value is close to zero. When the R^2 values are analyzed, the optimum R^2 value is obtained to be 0,0460 and this value expresses that the numerical relation between the actual schedule variation (%) values and the schedule variation (%) values obtained from the modeling is at the level of 4,60%, that is, the schedule variation (%) is estimated with a 4,60% accurateness in MLP model. The findings show that the MLP modeling falls short of estimating the schedule variation (%) for the Model 2.

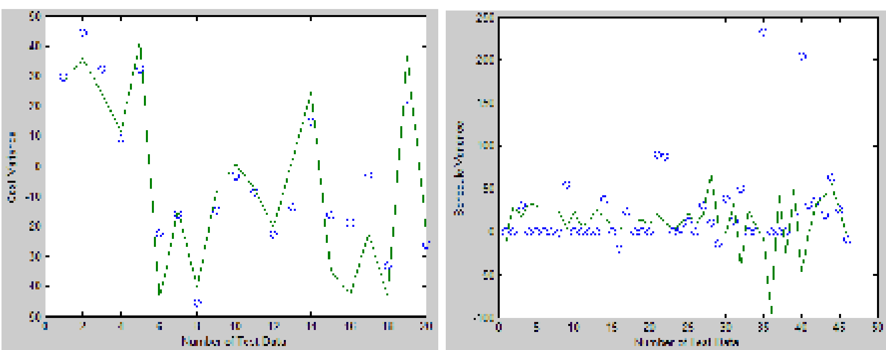
As for the GPA method, the second of the artificial intelligence methods used in the study, the optimum RMSE and R^2 values obtained during the testing stage of each combination by trying 192 variations for the Model 1 and 96 variations for the Model 2 in total for the stated value ranges in the previous part are shown in the Table 6.

Table 6 Test Results of Models by GPA Method

Model Nr.	Comb. Nr.	Number of MF	Input MF Type	Output MF Type	Iteration Number	RMSE	R^2
1	1	2	Triangle	Constant	5	26,4675	0,0290
	2	2	Gauss	Constant	5	27,9751	0,0012
	3	2	Triangle	Linear	5	**27,0446**	4,34e-033
	4	2	Triangle	Linear	5	27,0446	4,34e-033
2	1	2	Gauss	Constant	5	**49,9634**	0,0070
	2	3	Triangle	Constant	100	59,6878	0,0025

When the RMSE values obtained from the Model 1 are analyzed, the RMSE value in the combination 2 was found to be higher than those in the combination 1. As such, it can be said that approximate cost input as the second input decreased the error performance of the network. As for the combination 3 and 4, it is seen that the RMSE values were the same. In other words, the fourth input, cost variation according to approximate cost, does not have any effect on the performance of the network. The R^2 value was also quite low. The results show that the current GPA modeling is less successful than the MLP modeling in estimating the cost variation (%). When the RMSE values obtained from the second model is analyzed, the same outcome is also obtained. Obtaining higher R^2 and lower RMSE values from the combination 1 than the combination 2 may be interpreted in a way that the project schedule planned to be the second input that decreased the performance of the network. After all, it shows that the current GPA modeling fell short of estimating the schedule variations (%) compared to the MLP modeling.

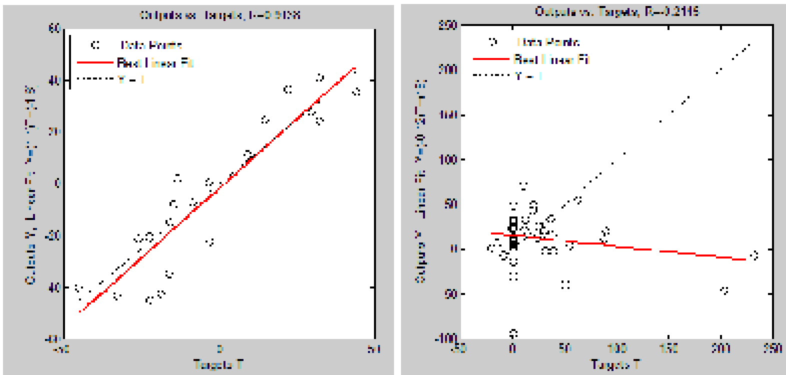
As widely known, error and accuracy have inverse proportions. In other words, as the error value decreases, the accuracy level of the model increases. Therefore, while comparing distinct estimation models, the model which has the lowest error value should be chosen as the best model. When the results of the RMSE of the two models analyzed through MLP and GPA methods, it is seen that the MLP models have lower RMSE values and thus greater accuracy rates. This means that MLP model shows a better performance in estimating the cost variation (%) and schedule variation (%) than GPA. The sequence graphics of the MLP modeling which gives the optimum results from Model 1 and Model 2 is given in Figure 5.



(a). Model 1 (b). Model 2

Figure 5 Sequence graphics of the MLP modeling

In figure 5.(a) the horizontal axis expresses each 20 data used during the testing stage according to their input sequence into the MATLAB software while the vertical axis refers to the cost variation (%) according to the approximate cost which is an output data of the model. In figure 5.(b), the horizontal axis represents the 47 data used during the testing stage while the vertical axis represents the schedule variations (%) according to the projected schedule which is an output data of the model. In both figures, the blue colored points refer to the actual data, while the green colored lines refer to the estimated values obtained from the model. The closer these to each other, the more successful the model is. Thus, it can be understood from Figure 5 that the Model 1 was more successful than the Model 2. The linear graphics of the models are provided in Figure 6.



(a). Model 1 (b). Model 2

Figure 6 Linear graphics of the MLP modeling

The horizontal axis in the graphics (T) states the actual values of the input data while the vertical axis (Y) states the estimated values obtained from the model. The red colored lines are the optimum lines adjusted according to the correlation between the actual values and the estimated values. The black lines are the lines that appear when the actual values and the estimated values are the same, that is the T=Y lines showing that the error rate is zero. The closer adjusted lines to the T=Y lines means that the model is successful. In Figure 6.(a), it is observed that the lines go close to each other. Therefore, it can obviously be stated that Model 1, in which cost variation (%) modeling according to the approximate value is done, was successful. In figure 6.(b), the placements of the lines differ. Therefore, it is seen that the Model 2 in which the schedule variation (%) modeling according to the projected schedule is done is relatively unsuccessful.

RESULTS AND SUGGESTIONS

In this study, the tender files of the 198 building projects in total were reviewed which were completed between 2004-2010 in Izmir, Turkey. As a result of the analyses, the projected and actual schedule and cost values are obtained and based on these values the cost variations (%) according to the approximate costs and schedule variations according to the projected schedule of each project are calculated. In application, principally unit cost method, which is widely used in Turkey, is dealt with and the approximate costs of each work are calculated in accordance with this method. By comparing the estimated approximate values, approximate values obtained through archive studies and actual costs, it is aimed to determine the accurateness of the unit cost method. The sum of the approximate costs obtained through unit cost method is found to be lower with a variation of 30% according to the sum of actual costs obtained from the archive studies and a variation of 19% according to the sum of approximate costs obtained from the archive studies. The variation rate by 19% can be interpreted to show that the unit cost method is far from the actual approximate cost estimation.

In application, as alternative methods MLP, which is a widely used ANN approach and GPA which is a hybrid approach, were used to analyze their applicability in estimating the cost and schedule variations in construction projects. For this purpose, two different models were created and the models were analyzed by using both artificial intelligence approaches. RMSE values have calculated 2,6476 and 9,0148 for Model 1 and Model 2 from MLP approach. RMSE values have also obtained as 27,0446 and 49,9634 from GPA approach. As a result, it was found that the MLP approach is better than GPA approach in its ability to estimate the cost variations (%) according to the approximate cost and schedule variations (%) according to the planned schedule of the project. Nevertheless, although satisfactory results are obtained through the network architecture in the form of (4-10-1) in estimating cost variation (%) estimation according to approximate cost through MLP approach, not valid results are obtained in estimating the schedule variations (%) according to the planned schedule of the project. The reason can be states as that the current schedule variation model consists of two combinations and with only two input data, realistic output results cannot be produced. By increasing the number of input data and thus the number of the combinations, analyses may be repeated during future studies.

After all, it is thought that when the abundance of factors that influence the cost variations during production and the complex process of the construction productions are taken into consideration, it is significant that an MLP model that consists of four inputs as the total construction area (m^2) approximate cost (TL), contract price (TL), and cost variation according to the approximate costs (TL) produces accurate and reliable results in estimating the cost variations (%) according to the approximate costs.

REFERENCES

[1] Baykan, U.N. (2007) İnşaat projelerinde kaynak ihtiyacının yapay sinir ağları yaklaşımı ile tahmini. *Gazi Üniversitesi Doktora Tezi*, Ankara, Turkey.

[2] Uğur, L.O. (2007) İnşaat firmalarının maliyet ve süre belirleme yöntemleri üzerine bir alan çalışması. *4. İnşaat Yönetimi Kongresi*, İstanbul, Turkey.

[3] Uğur, L.O. (2007) Yapı maliyetinin yapay sinir ağı ile analizi, *Gazi Üniversitesi Doktora Tezi*. Ankara, Turkey.

[4] Ashworth, A. (1999) Cost Studies of Buildings. *Longman Scientific & Technical*, Harlow, England.

[5] Polat, D.A. (2005) Türkiye'de tasarım öncesi evrede inşaat maliyeti tahmini için bir yöntem önerisi. *İnşaat Mühendisleri Odası İstanbul Bülteni*, **77**, 20-24.

[6] Siqueira, I. (1999) Neural network-based cost estimating. *Concordia University, Degree of Masters of Applied Science*, Canada.

[7] Kim, G.H., An, S.H. and Kang, K.I. (2004) Comparison of construction cost estimating models based on regression analysis, neural networks and case-based reasoning. *Building and Environment*, **39**, 1235-1242.

[8] Günaydın, H.M. and Doğan, S.Z. (2004) A neural network approach for early cost estimation of structural systems of buildings. *International Journal of Project Management*, **22**, 595-602.

[9] Turhan, N. (2006) Kamu ihale sistemindeki değişikliğin inşaat yatırımlarının süre ve maliyetlerine yansımaları. *Çukurova Üniversitesi Yüksek Lisans Tezi*, Adana, Turkey.

[10] Civelekoğlu, G. (2006) Arıtma proseslerinin yapay zekâ ve çoklu istatistiksel yöntemler ile modellenmesi. *Süleyman Demirel Üniversitesi Doktora Tezi*, Isparta, Turkey.

[11] Jain, A.K., Mao, J.C. and Mohiuddin, K.M. (1996) Artificial neural networks: A tutorial. *Computer*, **29**(3), 31-44.

[12] Kayadelen, C., Taşkıran, T., Günaydın, O. and Fener, M. (2009) Adaptive neuro-fuzzy modeling for the swelling potential of compacted soils. *Environmental Earth Sciences*, **59**, 109-115.

[13] Eren, B. And Eyupoglu, V. (2011) Yapay sinir ağları ile ni(II) iyonu geri kazanım veriminin modellenmesi, *6th International Advanced Technologies Symposium (IATS'11)*, Elazığ, Turkey.

[14] Singh, K.P., Basant, A., Malik, A. and Jain, G. (2009) Artificial neural network modeling of the river water quality-A case study. *Ecological Modelling*, **220**(6), 888-895.

[15] MATLAB, Version 7.1, The MathWorks Inc., Massachusetts, USA.

http:// www.mathworks.com