THE UTILIZATION OF ROBUST INTELLIGENT MODEL FOR PROJECT DURATION PREDICTION

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ABSTRACT

As a matter of fact, the duration of construction any project relies on several indicators such as site features, construction location, project cost, procurement methods and multiple other factors. Predicting construction project duration accurately is highly significant for completing project on time. In this research, the application of soft computing technique namely extreme learning machine (ELM) model is used to predict construction project duration. The study is carried out using several factors effecting the target duration of construction project. The implemented data set were obtained from department of construction and technical works at the Middle East Technical University. The proposed ELM model was verified in comparison with artificial neural network (ANN) model. The performance of the modeling accuracy was inspected using several statistical indicators such as coefficient of determination (*R*), root mean square error (*RMSE*), and mean absolute percentage error (*MAPE*). The findings of this research showed a very reliable and practical implementation for the ELM model in predicting construction project duration over the very well-known GRNN model. In more representable details, the enhancement of the (*RMSE* and *MAPE*) values for ELM model over ANN model were (51.5 and 50.8 %).

Keywords: construction project duration, reliable management, prediction problem, extreme learning machine, artificial neural network, intelligent models.

1. INTRODUCTION

Construction project time completion is highly important for contractors as well as the clients[1]. Incomplete projects with its stipulated duration can affects these parties and cause a lot of loses due to the increment in the project cost and other consequences on the clients' objectives. Hence, in order to keep any project activities within prestigious management, budget and quality, an accurate and reliable prediction for the project duration is highly essential for successful completion [2]. In accordance to effective accomplishment criterion, project duration prediction is vital for both contractors and customers prospective. Here, the customer can initiate finance, materials, and cash procedure plan in preset of time and establish an optimal for their targeted project. On the other hand, contractors can predict the progress of the construction accurately with performing works actions appropriately which lead to get control in the business development and give good decision precautions against postponements.

Project duration can be predicted in distinctive phases of the project achievement. This is in accordance to the tasks information accessibility and run time of the progress constraints, which are very important and critical for the project planning and management[3]. For instance, in the advance design stage, the determination of the construction duration is not easy task with the minimum available information. Those possibility of development might be very critical venture in construction development and thus clients need to recognize and be knowledgeable of the approximated duration and cost of a particular project.

Project management engineers adopted an approach called estimate at completion (EAC) as an automatic and quick method that assessing the project cost in accordance to the completed scheduled activities [4]. In this area, numerous studies have been conducted with various methodologies. One of the popular method is the stochastic S curves (SS curves) concept was used by Barraza and his colleagues to determine the estimate of forecasted projects rather than using the traditional forecasting and deterministic S curves methods [5]. The stochastic S curves are generated through a simulation approach based on the set changes in the cost and time of the respective activities within the process. Another very popular statistical environment called stochastic project scheduling simulation (SPSS) was first introduced and developed by Lee in 2005 [6]. The software was used to measure the possibility of completing a work within a specified period. The software determines the longest route in a network and runs the network severally as specified by the user to calculate the probability of completing the work within the designated period. The SPSS formed the basis of this system; it uses all the functionalities of this system. A new forecasting approach (probabilistic) for the control of scheduled performances and management of risks associated with on-going projects was developed by [7]. The approach (Bayesian beta S-curve method (BBM)) is principled on the Bayesian inference and the beta distribution. It offers bounds on the confidence of prediction which can be used for the determination of the probability of success and the range of possible results.

The area of soft computing models (e.g., artificial intelligence (AI)) which is mainly based on the learning of the relationship between the attributes to construct a single or multiple outputs, is ideally undertaken most recently for the current scope. Among several models of soft computing techniques artificial neural network[8–10], support vector machine[11, 12], evolutionary machine

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learning algorithms[12] are widely recognized techniques utilized for prediction project duration in the last decade. Since late 1990s, the application of soft computing models has been genuinely applied in the field of construction management and particularly in prediction duration and cost [13, 14], due to their potential in capturing the high stochasticity.

In 1994, the earliest attempt of the utilization of soft computing models in the field of project management conducted by Wu and Hadipriono [15]. The authors developed a fuzzy-logic model for construction project duration estimation. In this paper, a classification for the elements that affect duration component was established. These elements are including labor efficiency, management strategy, location of the project, facilities effectiveness, materials supply, and finally weather condition. The basic steps of this model are based on the trigonometric calculations, which are integrated into the Super Project software. The finding of this research concluded that durations activity is determined through the professionalism of planning in addition to fuzzy logic model could perform very excellent methodology for the investigated application. Based on the obtained results, the scholars indicated that the results influence from one case to another based on the phenomenon of the available information and the nature of the case study. Another study developed by Kumar and Reddy in 2005 [16],the researchers used the concept of fuzzy logic theory for achieving the objective to estimate the project parameters by incorporating the qualitative and quantitative factors for each activity. The results emphasize the utility of the soft computing in this field with very positive prospective. In general, the use of intelligence models in the field of construction project management has exhibited a very brilliant methodologies to solve the stochasticity and the uncertainty [9]. However, these applications still suffer from several drawbacks such as time-consuming learning mechanism, the problem of global minima, finding a generalization approach, and manual tuning. Exploring new and robust model as a predictive technique is the passionate of researchers.

Extreme learning machine (ELM) has been discovered most recently and applied in multiple research scopes in the last decade. The fundamental algorithm of this approach is trained using single hidden layer feed forward neural networks (SLFNs). The hidden nodes in the ELM are initiated randomly before fixing without any iterative tuning. These hidden nodes in the ELM do not even need to resemble the neurons. During the learning process, only the connections between the hidden layer and the output layer are needed to be learned. With this approach, the ELM is mainly formulated in a linear-in-the-parameter model for the solving of just linear system. The ELM is efficient and can reach a global optimum on the contrary with the traditional AI models. It has been proven that ELM maintains the universal approximation capability of SLFNs even with randomly generated hidden nodes[17].

The improvement of the prediction modeling through computational experiments using a non-tuned machine learning algorithm is the major aim of this study. The main objective of this study was to develop an intelligence model based on soft computing approach which can be implemented in real construction project management practice. The projection characteristics can be used by the contractors for the estimation of the exact time to complete a given project as provided in the tender documents.

2. METHODOLOGY

2.1 Extreme learning machine model

The ELM learning algorithm tool for the SLFN framework which randomly chooses the input weights for the analytical determination of the output weight of the SLFN [18]. The ELM has a faster learning speed and favorable characteristics, requiring less running time (by minimizing the manual interventions through analytically determining the network parameters) when compared to the traditional algorithms. Some of the benefits of using this algorithm are the ease of using it, the fast learning speed, the compatibility with several non-linear activation and kernel functions, as well as its superior performance when compared to the other algorithms. Over the past five years, the ELM has been successfully implemented in various application in the literature and approved its proficiency such as learning capacity for clustering, regression, feature learning, and classification application [19–23]. Up to the author knowledge, there is no single research has been undertaken the skill of ELM approach for modeling project duration, here where the novelty lies. In more detailed graphical presentation, Figure 1 shows the structure of the generalized ELM model. In accordance to the figure 1 conception, the input variables were the (i.e., total area of construction, total volume value, cost value, and facade area value) while the output variable was the construction project duration.

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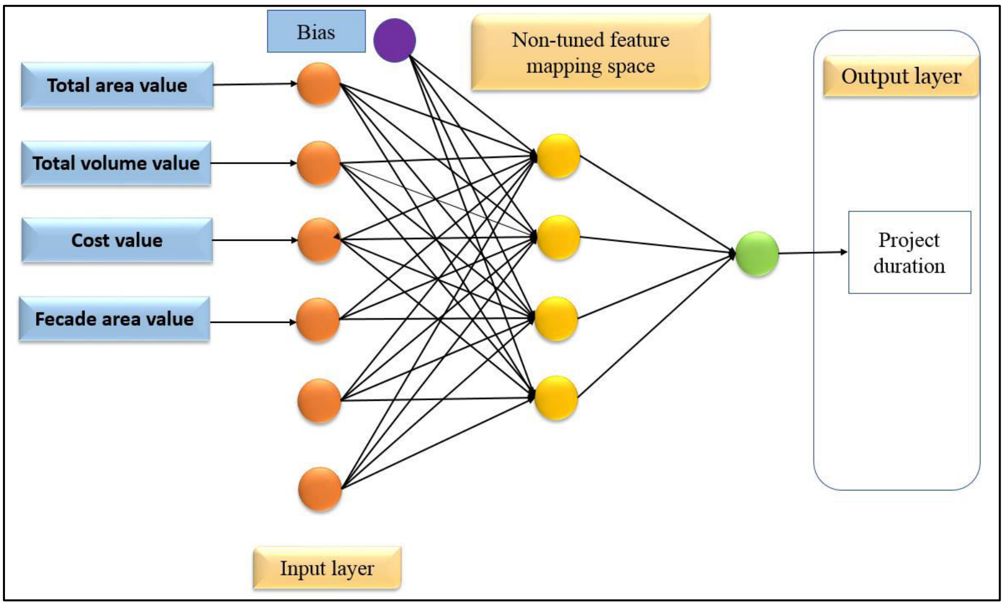

Figure-1. The non-tuned intelligent model (ELM) architecture description.

The input data is processed using the ELM model through the M-dimensional mapping feature space that randomly determined the internal weights while the output network is based on the following mathematical procedure [18]:

$$F(x) = \sum_{i=1}^{M} \beta_i h_i(x) \quad (1)$$

The variables of the formula are β_i is the output matrix weight that connected the hidden layer space and the targeted phase. h_i is the hidden nodes output for the input variables (x). Whereas, $M$is the ELM feature space dimension. The regression problem can be solved using the ELM learning processes via the following formula [18]:

$$H\beta = T \quad (2)$$

Here, the H represents feature space reported in formula (1) "hidden zone output matrix", $M.T$ defines the matrix target. The learning operation conducted by ELM model is to obtain the minimum error $Minimize: \|H\beta - T\|$ and $\|\beta\|$. The hidden output layer H can be indicated as follows:

$$H = \begin{bmatrix} h_1 x_1 & \cdots & h_M x_1 \\ \vdots & \ddots & \vdots \\ h_1 x_N & \cdots & h_M x_N \end{bmatrix} \quad (3)$$

2.2 Artificial neural network

Artificial neural networks (ANNs) are a parallel system that can processes information made up of a set of neurons that are arranged in layers manners [24]. ANNs are very well-known comprises of three layers including input, output and a sandwiched layer called hidden layer with several tuned neurons [25]. In each layer, the neurons are connected by weights to the neurons in the subsequent layers in the training phase. The sigmoid and the linear activation functions are commonly used in the hidden and output layer respectively, to analyze the features in an input data set. The most common and popular training algorithms have been used in the literature to solve regression problems are the Multi-layer perceptron (MLP) with a back-propagation algorithm [25–27], generalized regression neural network (GRNN), radial basis function (RBF). Based on the efficiency of the predictability of these algorithms, it was selected GRNN algorithm for this research as a comparable machine learning model. It is a supervised learning platform that has been used in the solving of several previous problems in prediction [28]. A further description of the MLP can be found in [29, 30].

2.3 Prediction evaluation metrics

The performances of the modeling are identified using several statistical metrics including coefficient of determination (R), Nash-Sutcliffe coefficient (NS), Willmott index (WI), mean absolute deviation (MAD), mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). The main point of conducting various evaluation metrics is to exhibit the prediction skills in more wide range of details. The mathematical description of these performance indicators can be exhibited as follows:

$$R = \frac{\sum_{i=1}^{n}[(D_a-\bar{D}_a)*(D_p-\bar{D}_p)]}{\sqrt{\sum_{i=1}^{n}(D_a-\bar{D}_a)^2 \ \sum_{i=1}^{n}(D_p-\bar{D}_p)^2}} \quad (4)$$

$$NS = 1 - \left[\frac{\sum_{i=1}^{n}(D_a-D_p)^2}{\sum_{i=1}^{n}(D_a-\bar{D}_a)^2}\right], \infty \le NS \le 1 \quad (5)$$

$$WI = 1 - \left[\frac{\sum_{i=1}^{n}(D_a-D_p)^2}{\sum_{i=1}^{n}(|D_p-\bar{D}_a|+|D_a-\bar{D}_a|)^2}\right], 0 \le NS \le 1 \quad (6)$$

$$MAD = \frac{1}{N}\sum_{t=1}^{n}|D_a - D_P| \quad (7)$$

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$$MSE = \frac{1}{N}\sum_{t=1}^{n}(D_a - D_P)^2 \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{n}(D_a - D_P)^2} \quad (9)$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{n}\left|\frac{D_a - D_P}{D_a}\right| * 100$$

3. CASE STUDY AND DATA DESCRIPTION

In this section, a description of the data set utilized as an application is presented. Project information including time duration, cost, and other project features (i.e., total area of construction, total volume value, fecade area value) were collected from the department of construction technical works, Ankara, Turkey. The span of the data set over a period of four years (2004-2007) that is belonging to five projects were subjected in the predictive models.

4. RESULTS AND APPLICATION DISCUSSIONS

In this section, the attained results of the prediction models were explained and discussed in detailed. While aiming to construct an intelligence model for solving a regression problem "in this paper, the prediction of construction project duration", the prediction was noticed to be characterized by several uncertain conditions. The large number of variable data that is involved in construction is the major source of the problem. Also, some factors that influence the duration of projects such as the physical site-productivity, the socio-economic conditions, and the weather conditions also contributes to the targeted variable. The prediction of these factors is a problem and often not practicable to evaluate them individually. The prediction model must, therefore, have the capability of coping with the large amount of factor influence and variable data to desirably predict the target variable.

The prediction of construction project duration is usually evaluated using numerical indicators such as the lower value of the absolute error or the largest value of fitness "regression close to 1". This is due to the fact that this kind of modeling based on two terms actual and predicted values. Through these performance indicators, a comprehensive comparison can be established to exhibit the out performance of the models. Tables 1 and 2 denoted the actual and predicted values of the five-investigated project using ELM and ANN models. The tables presented all the physical variables of construction including the total area, total volume, cost, fecade area, and finally a combination of all these variables as predictors for the project duration.

Table-1. Predicted project duration using ELM model over all the inspected physical variables and individually and in combination.

Projects	Actual duration	Total area value	Total volume value	Cost value	Fecade area value	All variables
A	354	322	361	343	364	348
B	265	211	256	258	242	260
C	260	289	248	268	251	269
D	242	223	221	249	258	237
E	200	218	189	209	213	211

Table-2. Predicted project duration using ANN model over all the inspected physical variables and individually and in combination.

Projects	Actual duration	Total area value	Total volume value	Cost value	Fecade area value	ALL
A	354	317	336	332	369	344
B	265	232	247	254	244	249
C	260	293	278	278	246	239
D	242	257	231	231	261	234
E	200	238	217	215	226	181

Tables 3 and 4 displayed the numerical metrics of the prediction skills. According to the obtained results using different variables, the proposed intelligent model ELM was able to predict the project duration more accurately than the tradition ANN model and consistently for all the variables runs. In quantitative measurements description, including all the construction variables in predicting the project duration yielded the best prediction performance for ELM and ANN models with (R and NS) values equal (0.99 and 0.97) and (0.99 and 0.90), and (RMSE and MAPE) are equal (7.58 and 2.92) and (15.63 and 5.94), respectively. A general observation, there was a gradual prediction skills augmentation by including all the examined variables as a one combination over the

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individual predictors. This is best can be justified in accordance to informative attributes supplied to the intelligent network that integrated the predictors with each other as they are connected with the aspect of management. Based on the performance skills tabulated in Tables 3 and 4, the enhancement of the (*RMSE* and *MAPE*) values for ELM model over ANN model were (51.5 and 50.8 %). Whereas, the augmentation percentages of (*R* and *NS*) values for ELM model over ANN model were slightly improved. This is due to the fact that these indicators highly influenced by the diversion among the actual and predicted values. In consistence, the regression scatter plot visualization of the predictive models indicated the out performance of the ELM over the ANN model, as displayed in Figures 2 and 3.

Table-3. The performance metrics results for ELM model including coefficient of determination (*R*), Nash-Sutcliffe coefficient (*NS*), Willmott index (*WI*), mean absolute deviation (*MAD*), mean square error (*MSE*), root mean square error (*RMSE*), mean absolute percentage Error (*MAPE*).

Variables	*R*	*NS*	*WI*	*MAD*	*MSE*	*RMSE*	*MAPE*
Total area value	0.79	0.56	0.79	30.4	1093.2	33.06	11.48
Total volume value	0.99	0.93	0.976	12	167.2	12.93	4.83
Cost value	0.98	0.971	0.897	8.4	72.8	8.53	3.24
Fecade area value	0.95	0.91	0.969	14.2	227	15.06	5.61
All variables	0.99	0.977	0.99	7.2	57.6	7.58	2.92

Table-4. The performance metrics results for ANN model including coefficient of determination (*R*), Nash-Sutcliffe coefficient (*NS*), Willmott index (*WI*), mean absolute deviation (*MAD*), mean square error (*MSE*), root mean square error (*RMSE*), mean absolute percentage Error (*MAPE*).

Variables	*R*	*NS*	*WI*	*MAD*	*MSE*	*RMSE*	*MAPE*
Total area value	0.78	0.58	0.783	31.2	1043.2	32.29	12.15
Total volume value	0.94	0.891	0.949	16.4	276.4	16.62	6.36
Cost value	0.95	0.899	0.95	15.4	255	15.96	5.86
Fecade area value	0.92	0.85	0.951	19	379.8	19.48	7.67
All variables	0.99	0.903	0.959	14.8	244.4	15.63	5.94

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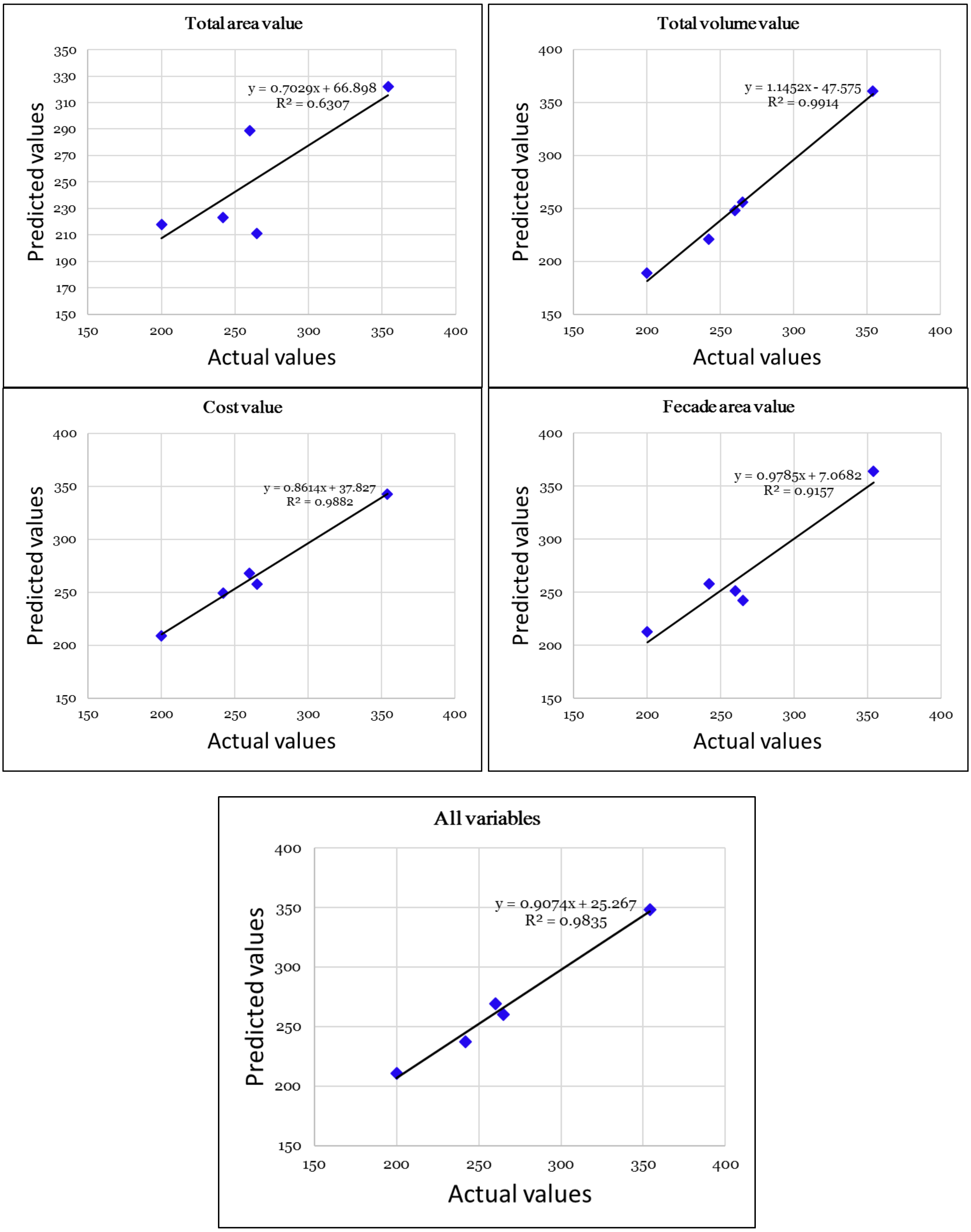

Figure-2. Scatter plot graphical presentation between actual and predicted construction project duration using extreme learning machine model.

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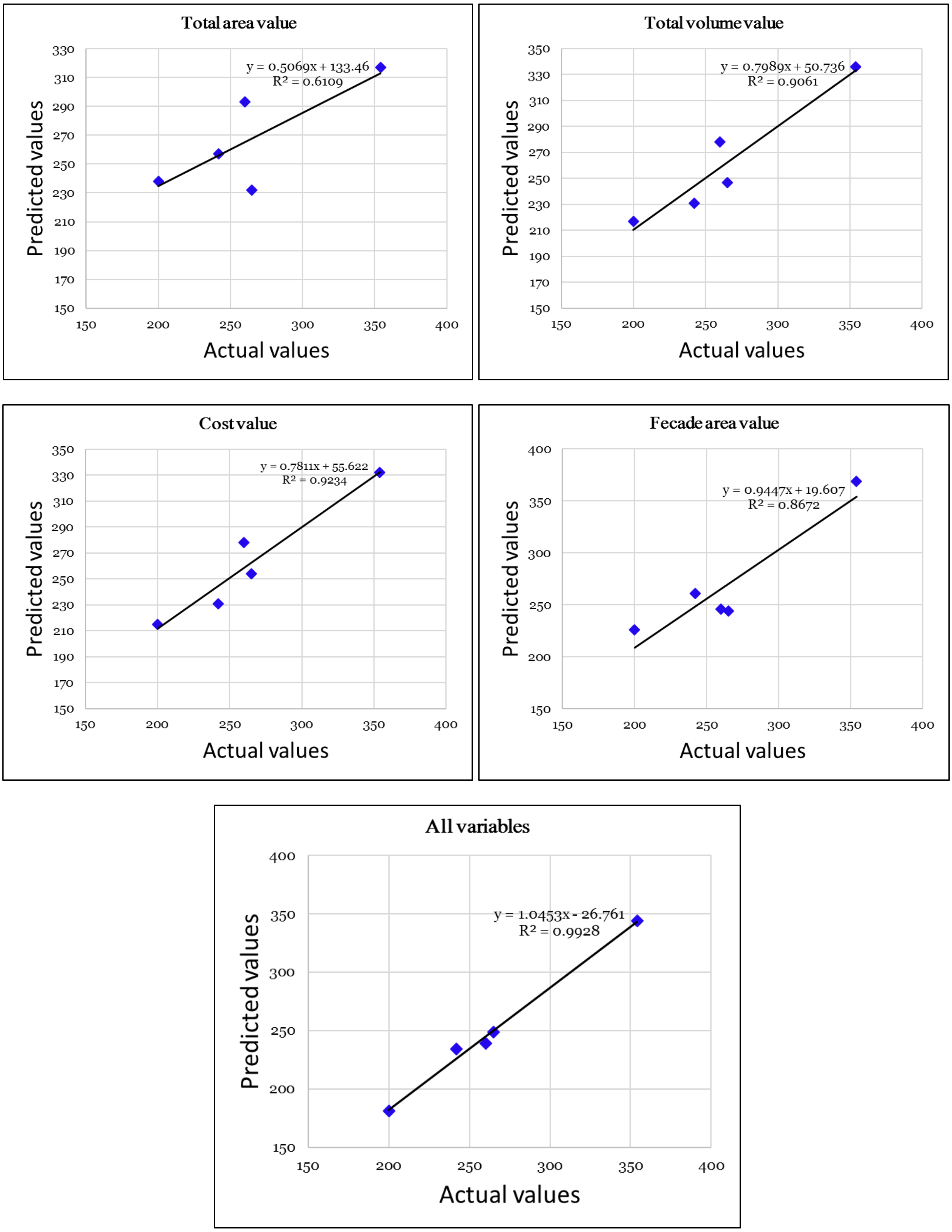

Figure-3. Scatter plot graphical presentation between actual and predicted construction project duration using artificial neural network model.

In the assessment of the prediction modeling, it has been used seven metrics. It was explicitly stated that each of these seven-metrics presented a robust assessment of the model. *RMSE*/*MAPE* were used to assess the overall error within the test dataset. It should be noted that *RMSE* is normally applicable if the distribution of error is Gaussian; however, this is not always the case. Hence, *MAPE* is also important when this condition of presentation is not very well visualized. However, the MAE is not weighted towards high(er) or low(er) magnitude values but instead evaluates all deviations of predicted from the actual values in an equal manner irrespective to the value indication (negative or positive) On the other hand, *NS* is crucial as it objects to assess the error in a normalized manner [31]. Fundamentally, this metric measures the ability to forecast data that deviate from the mean. As a ratio, this assesses the agreement between actual and predicted data, and is sensitive to the differences in actual and predicted means and variances. Finally, an employment for the *WI* was established. This metric can provide more advanced information than *NS*, since this metric does not square the differences between actual and predicted data[32, 33]. Specifically, *WI* (namely the ratio of the mean square error and potential error multiplied by the number of observations and then subtracted from one) aims to assess the differences based on squared differences.

5. CONCLUSIONS

In the current research, an intelligence model namely extreme learning machine is proposed to predict construction project duration. The significant of conducting this research owing to the necessity of establishing a reliable and robust predictive for the applied application and can be implemented practically. Five construction project features data set were collected from the department of construction technical works, Ankara, Turkey. To achieve this feat, several construction variables used to determine the project duration "the target variable". For the purpose of validation, classical intelligent model called artificial neural network was developed. Several performance metrics calculated including absolute error and fitness measurements. The implementation of the ELM model for the applied application was successfully established. The level of similarity between the predicted and actual values was enhanced significantly with the ELM model when compared to the ANN model. The utilization of the proposed non-tuned model can be used by the contractors to estimate the duration of construction and compare it with the duration earlier supplied by the client to check for the possibility of realizing the with the given budget ad at the specified time. Such modeling requires their own databases. This historical data based modeling approach of the contractor will be more concrete, practical, and reliable when compared to the subjective methods based on intuitive estimations that are currently been used by planners.

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