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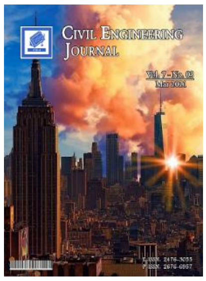

# Predicting Performance Measurement of Residential Buildings Using an Artificial Neural Network

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**Abstract**

Application Earned Value Management (EVM) as a construction project control technique is not very common in the Republic of Iraq, in spite of the benefit from EVA to the schedule control and cost control of construction projects. One of the goals of the present study is the employment machine intelligence techniques in the estimation of earned value; also this study contributes to extend the cognitive content of study fields associated with the earned value, and the results of this study are considered a robust incentive to try and do complementary studies, or to simulate a similar study in alternative new technologies. This paper is aiming at introducing a novel and alternative method of applying Artificial Intelligence Techniques (AIT) for earned value management of the construction projects through using Artificial Neural Networks (ANN) to build mathematical models to be used to estimate the Schedule Performance Index (SPI), Cost Performance Index (CPI) and to Complete Cost Performance Indicator (TCPI) in Iraqi residential buildings before and at execution stage through using web-based software to perform the calculations in the estimation quickly, accurately and without effort. ANN technique was utilized to produce new prediction models by applying the Backpropagation algorithm through Neuframe software. Finally, the results showed that the ANN technique shows excellent results of estimation when it is compared with MLR techniques. The results were interpreted in terms of Average Accuracy (AA%) equal to 83.09, 90.83, and 82.88%, also, correlation coefficient (R) equal to 90.95, 93.00, and 92.30% for SPI, CPI and TCPI respectively.

*Keywords:* Earned Value Management; Artificial Neural Network; Performance Index; Iraq.

## 1. Introduction

Generally, the measurement of performance has an essential position in the development management process. Performance size delivers the essential information to analyze factors for the owner, contractors, and management professionals to control the progression of the construction process, evaluate the future fees of any building project, and measure its competition in the international market. One of the most powerful and famous multilayers feed-forward network is trained with backpropagation. The developed community's coaching is performed using the backpropagation algorithm, which was once developed and entailed three stages; the feed ahead stages of the input training patterns, the calculation and backpropagation stage of the associated error, and the adjustment stage of the weights. This paper's primary goal is to develop the Artificial Neural Network (ANN) mannequins to predict the earned value of residential construction projects. To achieve the planned goal; it is essential to discover the elements influencing the performance of residential building projects. Therefore, the authors of this study focused on the

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development, and evaluate the performance of a model that predicts the earned value via the following steps: (a) Identification of model parameters that have an effect on the earned fee index in residential structures project using multiple linear regression techniques, which were performed using SPSS package, (b) Development and assessment of the performance of the proposed ANNs models to predict the earned cost and schedule indexes, and (c) Check the verification and validation of the mathematical models developed. In addition, it is creating, developing, and evaluating the web-based software to complete the calculation of the required forecasts for Earned Value Indexes quickly, easily, and with high accuracy. The prediction of site overhead costs with the use of an artificial neural network-based model was investigated [1]. This paper was to develop an alternative model that allows fast and reliable estimation of site overhead costs. The author concluded that the results of the authors' work on the development of a regression model, based on artificial neural networks, that enables prediction of the site overhead cost index, The neural network selected to be the core of developed model allows the prediction of the costs' index and aids in the estimation of the site overhead costs in the early stages of a construction project with satisfactory precision.

In this study, the main target is on using associate Artificial Intelligence Techniques for the aim of earned value prediction, meant as a decision-support aid to project managers, contractors, and planners. The contribution of this study is to spot the most effective activity in terms of model structures and parameters on an earned value prediction, the performance of the ANN is going to be compared with Regression Analysis (RA). As well as the research Originality can be summarized to get standard local equations of very high accuracy to predict the earned value indexes with less error, through the use of smart technologies in the activities of earned value management which saves a lot of time, effort and cost. These equations can be provided rapid solutions to the Iraqi project management agencies and authorities in earned value management. Research methodology has adopted to involve as shown in Figure 1.

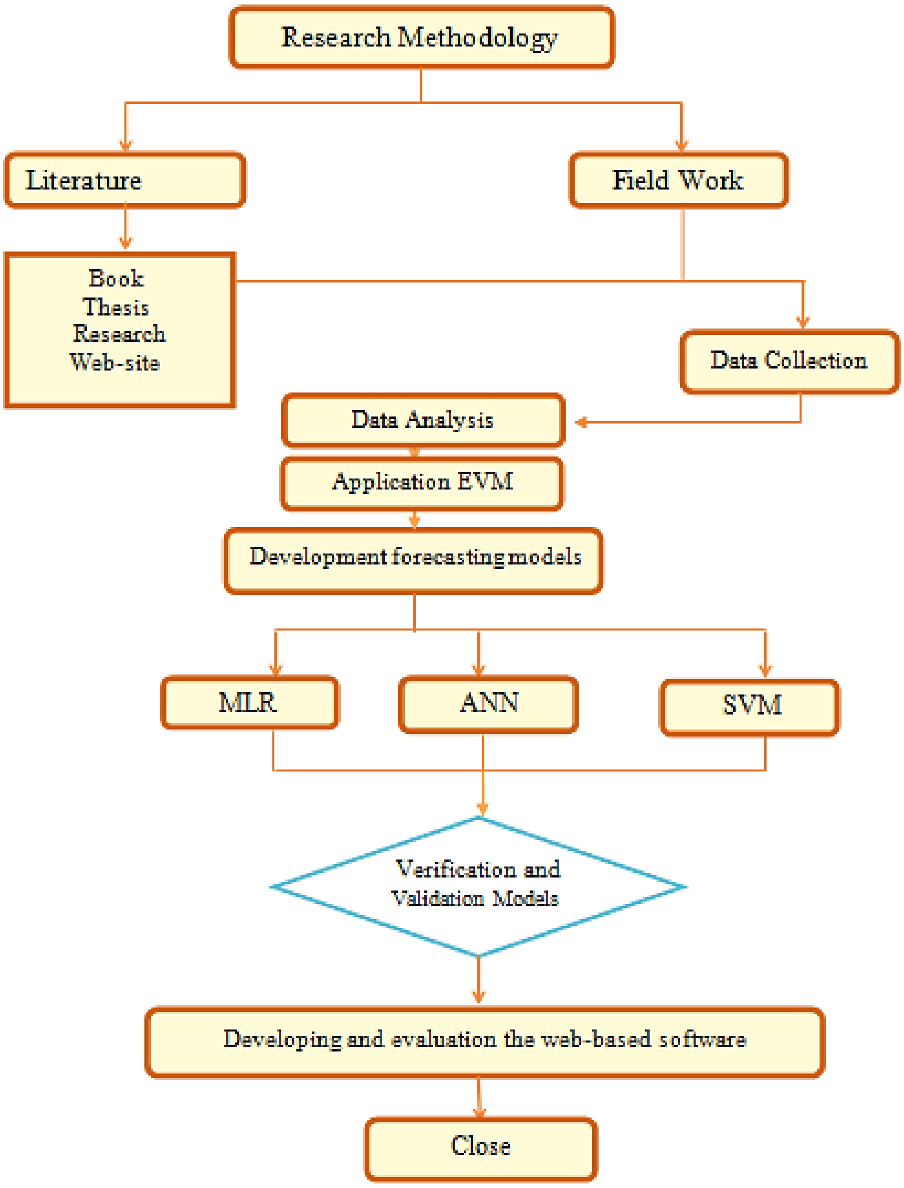


**Figure1. Research Methodology**

## 2. Background

EVM is a project management methodology that enables the professionals of project management to monitor the three components schedule, scope, and cost which they are combined by this methodology so, they have an objective measure of projects' construction. The aim is to minimize subjective progress measurement [1]. There are several definitions for Earned Value Management (EVM). The defined EVM as an as an efficient technique of integration the schedule, scope, and cost of the project [2]. Earned value management (EVM) is a helpful method that enables easy project control and delivers support in final estimating cost [3, 4]. Earned Value Management (EVM) is a management technique for project performance monitoring. EVM method delivers variances of performance and indexes that enable managers to notice over-costs and delays [5]. The EVM contains many techniques that target facilitating the measuring and assessment the performance and progression of the project by evaluation both of the completion cost and completion time of a project based on its actual cost and actual-time up to any given point in the project. The EVM is considered a measuring method of the cost of achieved works, and it provides an indication of how the project resources are utilized efficiently by the team of the project [6]. EVM is a reliable management system that enables professionals to calculate the cost, schedule differences, performance and prediction of project cost, and duration of the schedule.. EVM is named deviation analysis, which is used to measure the performance of projects and the progression of projects [7]. The earned value management (EVM) can be defined as a number of project management, and it is a methodology, not added tasks to be performed with the "normal" project management functions which are used to plan, implement, and evaluate how the project is performing against the plan Kim [8]. EVM technique just facilitates tasks, which the project manager should achieve one way or another. EVM technique is defined by the association Project Management as a good practice method which can be employed for planning, managing, and controlling projects and programs including the large and small programs, and the projects of internal companies. The method supports establishing a baseline plan and cost management for the project and integrated schedule performance to this plan. Earned value project management (EVPM), which is a technique that utilizes scope, cost, and schedule to determine, and link the real physical process of a project is the most commonly used of the project performance forecasting approaches reviewed [9, 10]. EVPM creates differences, indices of performance for project costs and schedules; therefore the first indications of expected outcomes of the project performance can be provided by predicting project costs and schedules at completion [11, 12].

Neural networks have different types, and these types have the simple clustering of Artificial Neurons (ANs). Neurons are grouped in one or many layers to form clusters, and the layers are connected. Their models have various methods of interconnection between network layers [13, 14]. The answer can be combined in different ways. There are two main types of neural network architectures shown as follow: (a) Feed-forward ANNs enable signal to transfer from input to output (one way only). No feedback (loops) i.e. the output of any layer does not affect that same layer. Such a neural class includes one or more layers of hidden units between the input and the output layer. The perceptron is a neuron with a transfer function and an adaptive weight mechanism (learning) by comparing the actual and the desired output for any input. Multilayer perceptions are a type of FFNNs, which consists of several neurons grouped in layers. It is include three types of layers, the layer that sends the input data to another layer in a forward direction, and unobserved layer which transfers data from the input nodes to the output nodes (also it makes the network able to learn complicated functions) and output layer, which provides the actual response of ANN. Figure (2) shows the structure of the MLP with one hidden layer.

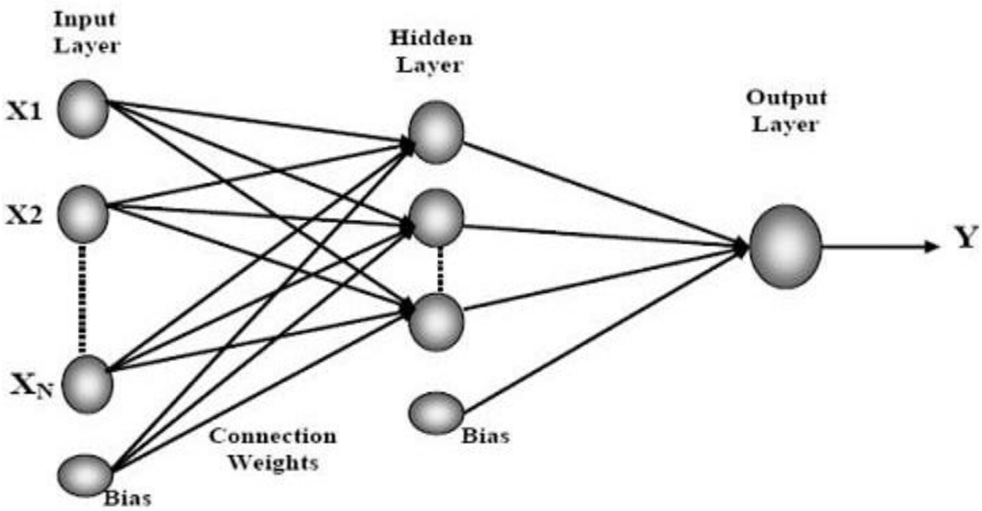


**Figure 2. Multilayer feed-forward neural network [2]**

The operation of the MLP network can be split into two phases: a training phase in which the MLP trained using training algorithms and a retrieval phase that generates output by using the previously trained MLP networks. MLP networks are training using a supervised algorithm with one hidden layer, and a sufficient number of hidden nodes (having the nonlinear transfer function) can produce feasible function to any desired rate of accuracy [15, 16].

More of researchers investigated neural network modeling for a two-stage production process with versatile variables: predictive analysis for above-average Performance. This paper uniquely presents an output-focused back propagation neural network (BPNN) approach with capabilities to capture patterns of high performers. They found the intelligent learning model advances existing two-stage production modeling with a methodological breakthrough and makes significant contributions to the existing literature [17].

Table 1 shows a comparison between the current study and the previous studies, where the current study aimed to introduce a statistic intelligent approach for earned value management of the residential complexes projects in the ministry of construction and housing in the Republic of Iraq. ANN systems have many advantages over traditional methods of modeling in situations where the process to be modeled is complex to the extent that it cannot be explicitly represented in mathematical terms or that explicit formation causes loss of sensitivity due to over-simplification.

**Table 1. Comparison between the current study and the previous studies**

| **Previous studies** | |
|---|---|
| Research Location | International studies have conducted in Arabic and foreign countries. |
| Research Aim | Investigate the EVM status and Application some techniques for predicting with only one of the indicators of EVM |
| Research Population | Most of the studies are addressed by construction projects, organizations, and companies. |
| Research Case Study | Bridges projects, highway projects, Building Projects, Waste Water Treatment Plant. |
| Research Tools | Most previous studies have used MLR, ANN, and SVM techniques separately and not integrated. |
| Software | SPSS and MATLAB. |
| **Current studies** | |
| Research Location | Iraq |
| Research Aim | The main aim of this research is to introduce a novel approach of using artificial intelligence techniques (MLR, ANN, and SVM) these are integrated into predicting indicators of Earned Value Management. |
| Research Population | Residential complexes projects in the Iraqi construction sector. |
| Research Case Study | Directorate of Housing / Ministry of Construction and Housing in the Republic of Iraq. |
| Research Tools | Historical Data, archives, direct observation, MLR models, ANN models, and SVM models are integrated. |
| Software | Software Statistical Package Social Science (SPSS), Microsoft Project, Neurosciences Neuframe 4.0, and Weka Software |

## 3. Identification of Model Variables

The historical facts included the six independent variables were selected, which have been well defined for every of residential structures projects, and three dependent variables used to be selected, where the case study is the residential complex project. Moreover, these factors that impact the overall performance of earned price for the residential buildings have adopted in Model ANN. There are two sorts of parameters that have an impact on the earned cost, which are established parameters and Independent parameters, as follows. Dependent parameters: Cost Performance Index (CPI), Schedule Performance Index (SPI), and to Complete Cost Performance Indicator (TCPI) are defined as the dependent parameters, and each individual project is used as the basic unit of the observation. Independent Variables: After establishing the dependent variables, which are to be predicted by the MLR technique, it was essential to develop independent variables to explain any variation in earned value indexes. There are many parameters as independent parameters such as: F1: BAC, Budget at Completion, F2: AC, Actual Cost, F3: A%, Actual Percentage, F4: EV, Earned Value, F5: P%, Planning Percentage, and F6: PV, Planning Value.

## 4. Development and Assessment of the Proposed ANN Models

Artificial Neural Network (ANN) models must be applied in a systematic manner to enhance their performance. Such method desires to tackle major elements such as development of model inputs, statistics division and pre-processing, development of mannequin architecture, mannequin optimization (training), stopping criteria, and model validation. A structured methodology for creating the model has been used to clear up the hassle at hand. This methodology contains five most important phases: (a) Model inputs and outputs, (b) Data division, (c) Model architecture, (d) ANNs Model Equation, and (e) ANNs Model Validity. In this research, it was once chosen Neuframe Program, where Neuframe is the premier neural community simulation environment. New frame range offers an easy-to-use, visual, object-oriented method to problem fixing the usage of smart technologies. It affords facets to enable companies to look into and follow wise technologies from initial experimentation via building embedded functions using software program components. There are three types of mathematical models, and their specific description can be concluded in the following sections: The variables that had been recognized at the facts identification stage had been used to boost the ANN models. Three mathematical models have been developed in this paper, the task characteristics in a mathematical mannequin were used to predict earned value indexes. NEW FRAME version four has been employed as a tool to boost the three models, as follows:

(a) Schedule Performance Index (SPI), (b) Cost Performance Index (CPI), and (c) To Complete Cost Performance Indicator (TCPI).

### 4.1. Schedule Performance Index (SPI) Model

#### 4.1.1. Development of Model Inputs and Outputs

The accuracy of the model entered factors that influencing considerably on the model's overall performance is a necessary step in growing ANN models. Presenting a massive wide variety of input parameters to ANN models normally will increase the network size, and that will reduce both of the processing pace and the network affectivity. Different methods have been recommended to aid the selection of input variables, such as a method of prior knowledge: depend totally on prior knowledge, the fabulous enter variables can be selected. This method is generally utilized in the area of task management and is adopted in this study. As a preliminary stage to neural community modeling, the trouble at hand requires to pick out and tag the statistics as entering or as output. New frame v.4 gives Microsoft Excel sheet, which is employed in this step. The unbiased elements affecting the hassle are recognized and viewed as (N) enter parameters, which are represented through nodes at the enter buffer of a neural network. The output of the model is the Schedule Performance Index (SPI), and the center of this model is Earned Value (EV) and Planned Value (PV).

#### 4.1.2. Data Division SPI Model

Data pre-processing is very essential for the use of neural nets successfully. It determines what information is introduced to create the model at some point in the training phase. So, the subsequent step in the development of ANN models is to split the accessible records into three subsets, training, testing, and validation sets. Learning is performed on the training set, which is employed for estimating the weights whilst the cross-validation set was employed for generalization that and for producing better output for unseen examples. However, to determine the generalization ability of the network and assess the performance of the network, the test set is employed for this purpose. In this step inside the improvement of ANN models. The on-hand information is split into three sections, which are training, testing and validation sets. The division process could be achieved by conducting the tries and obtaining the minimum testing error and the perfect coefficient correlation. Neuframe software could be employed to complete this division. The community that recognizes testing errors and performs greatly is used in this work (as compared with variant limits to consider the prediction performance, education error, and correlation of validation set). Using the default parameters of the software; a range of networks with the unique divisions that had been developed. The outcomes are listed in Table 2.

**Table 2. Impact of Data Division on SPI Model Performance**

| Data Division % | | | Training Error % | Testing Error % | Coefficient Correlation (r) % |
|---|---|---|---|---|---|
| Training | Testing | Querying | | | |
| 60 | 23 | 17 | 6.40 | 6.70 | 75.00 |
| 65 | 20 | 15 | 6.40 | 6.60 | 74.00 |
| 70 | 15 | 15 | 5.90 | 6.00 | 80.00 |
| 75 | 10 | 15 | 5.50 | 5.90 | 85.31 |
| 75 | 15 | 10 | 5.40 | 5.70 | 88.00 |
| 80 | 10 | 10 | 5.30 | 5.30 | 90.95 |
| 85 | 10 | 5 | 18.00 | 5.40 | 90.80 |
| 85 | 5 | 10 | 18.00 | 5.40 | 90.70 |

According to Table 3, the quality division is 80% for the coaching set, 10% for the trying set, and 10% for the validation set, the taken checking out error and coefficient of correlation (r) 5.30 and 90.95% respectively. Thus, this division was once ordinary in the SPI model. The impact of the use of one-of-a-kind preferences for divisions (i.e. blocked, striped, and random) was investigated and proven in Table 3. It should be noticed that the overall performance of the ANN model did not affect by changing the method of division. The maximum performance was attended when the striped division was used.

**Table 3. Effects of Method of Division on SPI Model Performance**

| Data division % | | | Choices of Division | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|---|---|
| Training | Testing | Querying | | | | |
| 80 | 10 | 10 | Blocked | 7.40 | 9.90 | 85.00 |
| 80 | 10 | 10 | Striped | 5.30 | 5.30 | 90.95 |
| 80 | 10 | 10 | Random | 6.50 | 7.70 | 88.00 |

#### 4.1.3. Model Architecture

One of the most important and challenging tasks in the development of ANN models is to decide the architecture of the model. Generally, there is not an exact method to determine the best numbers of neurons in every hidden layer. The increasing of hidden layers in the network makes trouble more difficult. The community of SPI Model is set for one hidden layer using the default parameters of the software program (learning price equal to 0.2 and momentum time period equal to 0.8 and the switch functions in hidden and output layer node are sigmoid), different of networks with various numbers of hidden layer nodes are developed. The outcomes are listed in Table 4, considering the maximum number of nodes equal to (2i+1) where (i) is the wide variety of input nodes. (i.e. most nodes equal to five).

**Table 4. Effect Number of Nodes on SPI Model Performance**

| Model No. | No. of Nodes | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|
| 1 | 1 | 5.30 | 5.30 | 90.95 |
| 2 | 2 | 5.40 | 5.90 | 90.19 |
| 3 | 3 | 5.90 | 6.50 | 87.45 |
| 4 | 4 | 6.30 | 6.80 | 86.87 |
| 5 | 5 | 6.78 | 6.90 | 85.62 |

Thus, one hidden node was once chosen in this model. It shows lowest value of testing error (5.30 %). According to the consideration of the optimal community, when the community includes one hidden node, then it is optimal. Therefore, this community was selected in this model. The impact of the momentum term on model overall performance used to be investigated for the model with one hidden node (learning rate equal to 0.20). The outcomes are listed in Table 5. The superior value for the momentum period is (0.80), which shows the minimum testing error equal to (5.30%), as a result, it was applied in this model.

**Table 5. Effect Momentum Term on SPI Model Performance**

| Momentum Term | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|
| 0.10 | 7.70 | 8.30 | 80.30 |
| 0.20 | 7.60 | 7.70 | 83.30 |
| 0.30 | 7.50 | 7.50 | 81.80 |
| 0.40 | 6.30 | 6.60 | 87.40 |
| 0.50 | 6.30 | 6.40 | 87.90 |

Then, the checked mistakes were barely minimize at the range between (0.80) and (0.95). Thus, the acquired greatest price for the momentum time period is (0.80), which has the cost of training error (5.30%) and enormous lowest value of trying out error (5.30 %) and maximum correlation coefficient (r) (90.95 %), as a result, it was once used in this model. Additionally, the impact of the mastering price on the model performance is used to be investigated (momentum period equal to 0.80) for the SPI Model. The outcomes are listed in Table 6. The ideal price forgetting to know the fee is (0.20), which has the lowest prediction error equal to (5.30%); for this reason, it is used to be applied in this model.

**Table 6. Effects Learning Rate on SPI Model Performance**

| Learning Rate | Testing % Error | Testing % Error | Coefficient Correlation (r)% |
|---|---|---|---|
| 0.10 | 6.76 | 5.35 | 90.95 |
| 0.20 | 5.30 | 5.30 | 90.95 |
| 0.30 | 6.34 | 5.93 | 90.01 |
| 0.40 | 6.77 | 5.99 | 90.21 |
| 0.50 | 6.98 | 6.20 | 90.08 |
| 0.60 | 7.76 | 6.30 | 88.28 |
| 0.70 | 7.54 | 6.50 | 89.56 |
| 0.80 | 8.44 | 6.80 | 87.85 |
| 0.90 | 8.49 | 6.90 | 85.56 |
| 0.95 | 8.68 | 7.10 | 84.54 |

Thus, the gained the best value for the learning rate is (0.2), which shows the significant value of testing error, significant value training error, and highly significant coefficient of correlation (90.95%); therefore, it was applied in this model. The impacts of applying various transfer functions (i.e. sigmoid and tanh) were investigated and it was shown in Table 7, it could be concluded that the performance of ANNs model comparatively did not affect by changing the kind of the transfer function. The best performance was attended when the sigmoid transfer function was applied for hidden and output layers, which has the lowest prediction error, 5.30% along with the maximum correlation coefficient (r) (90.95%).

**Table 7. Effect of Transfer Function on SPI Model Performance**

| Transfer function | | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|
| Hidden Layer | Output Layer | | | |
| Sigmoid | sigmoid | 5.30 | 5.30 | 90.95 |
| Sigmoid | Tanh | 6.56 | 6.33 | 89.99 |
| Tanh | sigmoid | 6.55 | 6.26 | 85.39 |
| Tanh | Tanh | 5.78 | 7.16 | 84.64 |

### 4.1.4. SPI Model Equation

A few number of connection weights were attended by Neuframe for the best SPI model. It is enabling the network to be transformed into a moderately modest formula. Figure 3 shows the arrangement of ANN model; also the weights of connection and levels threshold are listed in Table 8.

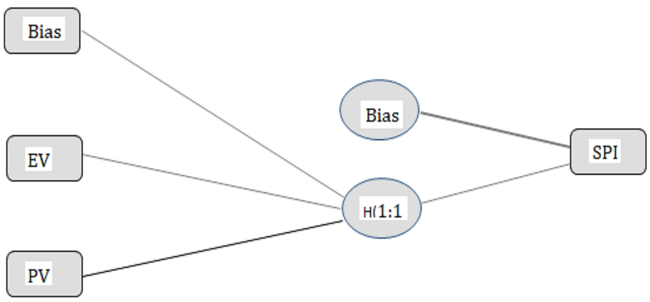


**Figure 3. Architecture of SPI Model**

**Table 8. Weight and Threshold Levels for the SPI Optimal**

| Weight from node I in the input layer to node j in hidden layer | | |
|---|---|---|
| F4 | F6 | SPI |
| 4.933 | -3.133 | 6.090 |
| **Hidden layer threshold $\Theta_j$** | | **Output layer threshold $\Theta_j$** |
| -1.236 | | -2.888 |

By applying the connection weight and the threshold levels listed in Table 7, the prediction of the SPI could be represented as follows:

$$SPI = \frac{0.535}{1 + e^{[2.888 - 6.09 \times \tanh(x)]}} + 0.714 \quad (1)$$

$$X = -1.236 + 4.933 \times 10^{-6} \times \text{F4} - 3.133 \times 10^{-6} \times \text{F6} \quad (2)$$

Where: $X$ is the weight and threshold values, F6 is EV, Earned Value.

A numerical example has been provided to have a better understanding of the application of the formula. The equation was examined against the data used in the ANN model training (SPI. Model). Where EV equal to 303616250 ID and PV equal to 390363750 ID. A good agreement was noticed between the estimated value using Equation 1 and the measured value that were 0.78907 and 0.77778, respectively (case no.1).

## 4.2. Cost Performance Index (CPI) Model

Follow the researcher five steps in building this model and as follows:

### 4.2.1. Development of Model Inputs and Outputs

The independent parameters that are affecting the problem, are identified and considered as (N) input variables, which are represented by nodes at the input buffer of a neural network. The output of the model is the Cost Performance Index (CPI), and the input of this model is Earned Value (EV) and Actual Cost (AC).

### 4.2.2. Data Division CPI Model

In the development of the ANN model, the available data is split into three subsets: training, testing, and validation sets. Thus, the inputting process of data into the Neuframe software was done using the default variables that resulted in many networks with various divisions. Table (8) illustrates the outcomes where the best division for the training set, testing set, and the validation set were 65, 15 and 20% respectively. Therefore, the accuracy of this division was approved in the CPI model basing on the obtained testing errors and correlation coefficient (r).

**Table 9. Effect of Data Division on CPI Model Performance**

| Data Division % | | | Training Error% | Testing Error% | Coefficient Correlation (r)% |
|---|---|---|---|---|---|
| Training | Testing | Querying | | | |
| 50 | 25 | 25 | 8.96 | 7.20 | 66.50 |
| 55 | 25 | 20 | 8.56 | 7.73 | 63.50 |
| 55 | 20 | 25 | 8.86 | 7.35 | 67.50 |
| 60 | 20 | 20 | 8.76 | 7.45 | 73.50 |
| 60 | 30 | 10 | 8.75 | 6.35 | 77.50 |
| 60 | 10 | 30 | 7.45 | 6.25 | 85.00 |
| 65 | 15 | 20 | 7.50 | 6.60 | 93.00 |
| 65 | 20 | 15 | 6.15 | 6.75 | 90.70 |
| 70 | 15 | 15 | 7.65 | 6.85 | 8860 |
| 70 | 20 | 10 | 7.75 | 7.60 | 88.50 |
| 70 | 10 | 20 | 7.75 | 7.65 | 82.30 |
| 75 | 10 | 15 | 8.85 | 7.65 | 83.30 |
| 75 | 15 | 10 | 8.85 | 8.65 | 84.10 |

The impact of using various selections for divisions (i.e. blocked, striped, and random) was investigated and the outcomes are illustrated in Table 10. The presentation of the CPI model comparatively was not affected by changing the method of division. The using of striped division shows a better presentation, and that could be observed below:

**Table 10. Effect of Method of Division on CPI Model Performance**

| Data division % | | | Choices of Division | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|---|---|
| Training | Testing | Querying | | | | |
| 65 | 15 | 20 | Blocked | 6.8 | 7.7 | 88.89 |
| 65 | 15 | 20 | Striped | 7.50 | 6.60 | 93.00 |
| 65 | 15 | 20 | Random | 8.5 | 9.5 | 80.85 |

### 4.2.3. Model Architecture

The network of CPI model is set to one hidden layer with using the default parameters of the software (learning rate equal to 0.2 and momentum term equal to 0.8 and the transfer functions in hidden and output layer node are sigmoid), many of networks with various numbers of hidden layer nodes is developed, and the outcomes are listed in Table 11. The highest number of nodes equal to (2I+1) where (I) is the number of entered nodes. (i.e. maximum nodes equal to 5). Due to the marginal variances in testing errors, two hidden nodes were selected in this model with the minimum testing error (6.60%). According to the requirements of the optimum network, this network was selected in this model because it has two hidden nodes.

**Table 11. Effect No. of Nodes on CPI Model Performance**

| Model No. | No. of Nodes | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|
| 1 | 1 | 7.50 | 6.80 | 91.95 |
| 2 | 2 | 7.50 | 6.60 | 93.00 |
| 3 | 3 | 8.80 | 7.50 | 89.55 |
| 4 | 4 | 8.80 | 7.60 | 87.88 |
| 5 | 5 | 8.90 | 7.70 | 86.85 |

The effect of the momentum term on model performance was studied for the model with two hidden node (learning rate equal to 0.20). The outcomes are listed in Table 12. It could be noticed that the best value for the momentum term is (0.7), which shows the minimum testing error; therefore it was applied in this model.

**Table 12. Effect Momentum Term on CPI Model Performance.**

| Momentum Term | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|
| 0.1 | 8.30 | 7.50 | 90.85 |
| 0.2 | 8.4 | 7.5 | 90.85 |
| 0.3 | 7.9 | 7.6 | 91.86 |
| 0.4 | 7.9 | 7.6 | 91.86 |
| 0.5 | 7.7 | 7.7 | 92.88 |
| 0.6 | 7.6 | 7.7 | 92.88 |
| 0.7 | 7.50 | 6.60 | 93.00 |
| 0.8 | 7.50 | 6.60 | 93.00 |
| 0.9 | 7.50 | 6.60 | 93.00 |
| 0.95 | 7.50 | 6.60 | 93.00 |

According to Table 12, the presentation of the CPI model does not affect comparatively by the change of the momentum term values, in particular a range of 0.1 to 0.7. Then, marginal growth in the test errors values is noticed at the momentum term values between 0.2 and 0.6 then stabled in 6.60 at the momentum term equal to 0.7. Therefore, the best-attended value for the momentum term is 0.7, which has the value of training error, minimum value of testing error and biggest correlation coefficient (r) 7.5, 6.6, and 93.00% respectively. Thus it was applied in this model. Additionally, the impact of the learning rate on the model performance was studied (momentum term equal to 0.7) for CPI Model. The outcomes are listed in Table 13. The best value for the learning rate is 0.2, which shows the minimum estimation error; therefore, it was applied in this model.

**Table 13. Effect Learning Rate on CPI Model Performance.**

| Learning Rate | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|
| 0.1 | 7.50 | 6.60 | 93.00 |
| 0.2 | 7.50 | 6.60 | 93.00 |
| 0.3 | 7.4 | 6.6 | 93.00 |
| 0.4 | 7.6 | 6.6 | 93.00 |
| 0.5 | 7.6 | 6.6 | 93.00 |
| 0.6 | 7.6 | 6.6 | 92.92 |
| 0.7 | 7.6 | 6.4 | 92.94 |
| 0.8 | 7.5 | 6.5 | 92.96 |
| 0.9 | 7.7 | 6.5 | 92.85 |
| 0.95 | 8.1 | 6.5 | 92.86 |

According Table 13, the performance of the CPI model does not affect comparatively by the change of the learning rate. The best-gained value for the learning rate is 0.2, which has the significant value of testing error equal to 6.6%, considerable value training error is 7.5%, and highly significant coefficient of correlation 93.00%. Therefore, it was applied in this model. The impacts of using various transfer functions (i.e. sigmoid and tanh) were studied, and the results are illustrated in Table 14; the performance of the CPI model did not affect comparatively by changing the kind of the transfer function. The best performance was attended when the sigmoid transfer function was used for hidden and output layers, which has the minimum estimation error 6.6%, along with the highest correlation coefficient correlation coefficient (r) equal to 93.00%.

**Table 14. Effect of Transfer Function on CPI Model Performance**

| Transfer Function | | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|
| Hidden Layer | Output Layer | | | |
| Sigmoid | Sigmoid | 7.50 | 6.60 | 93.00 |
| Sigmoid | Tanh | 9.50 | 6.90 | 90.00 |
| Tanh | Sigmoid | 8.50 | 7.80 | 89.90 |
| Tanh | Tanh | 8.50 | 8.50 | 84.80 |

#### 4.2.4. CPI Model Equation

A limited number of connection weights were attended by Neuframe for the optimal CPI model. It is enabling the network to be transferred into a moderately modest formula. Figure 4 shows the arrangement of the ANN model; also the weights of connection and levels threshold are listed in Table 15.

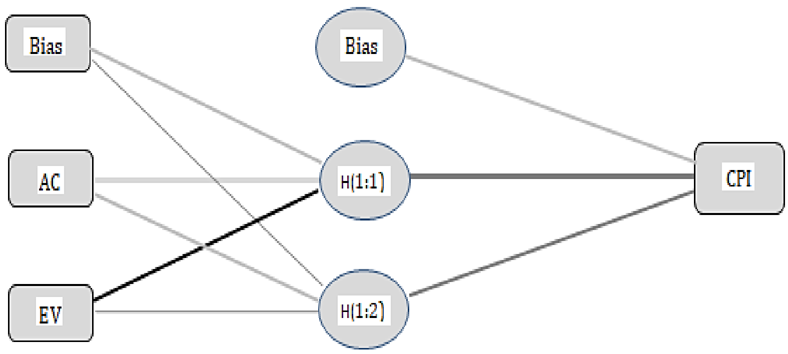


**Figure 4. Architecture of CPI Model**

**Table 15. Weight and Threshold Levels for the CPI Optimal**

| Predictor | | Predicted | | |
|---|---|---|---|---|
| | | Hidden Layer 1 | | Output Layer |
| | | H(1:1) | H(1:2) | CPI |
| Input Layer | (Bias) | -0.004 | -0.524 | |
| | AC | -1.865 | 5.664 | |
| | EV | 2.630 | -3.534 | |
| Hidden Layer 1 | (Bias) | | | 1.086 |
| | H(1:1) | | | 3.880 |
| | H(1:2) | | | -6.784 |

By applying the connection weight and the threshold levels illustrated in Table 14, the prediction of the equation total cost could be represented as follow:

$$\mathrm{CPI} = 1.315298/(1 + e^{[-1.086 - 3.88\times \tanh(X1) + 6.784\times \tanh(X2)]}) + 0.742 \tag{3}$$

$$X1 = -0.004 - 1.865 \times 10^{-6} \times \mathrm{F2} + 2.63 \times 10^{-6} \times \mathrm{F4} \tag{4}$$

$$X2 = -0.524 + 5.664 \times 10^{-6} \times \mathrm{F2} - 3.534 \times 10^{-6} \times \mathrm{F4} \tag{5}$$

Where: *X1* and *X2* are the weights and threshold values, F2: AC, Actual Cost, F4 is EV, Earned Value,

A numerical example has been provided to have a better understanding of the application of the formula. The equation was examined against the data used in the ANN model training (CPI. Model). Where EV equal to 303616250 ID and AC equal to 308071875 ID, a good agreement can be noticed between the predicted value using Equation 3 and the measured value, that were equal to 1.057 and 0.98554 respectively (case no.1).

### 4.3. To Complete Cost Performance Indicator (TCPI) Model

Follow the researcher five stages in building this model and as follows:

#### 4.3.1. Development of the Inputs and Outputs of the Model

The independent variables affecting the problem, are identified and considered as (N) input variables, which are represented by nodes at the input buffer of a neural network. The output of the model is To Complete Cost Performance Indicator (TCPI), and the input of this model is Earned Value (EV) and Actual Cost (AC).

#### 4.3.2. Data Division TCPI Model

In the development of the ANN model, the available data was split into three subsets, which are training, testing, and validation sets. Thus, the inputting process of data into the Neuframe software was done using the default variables that resulted in many networks with various divisions. The outcomes are listed in Table 16.

**Table 16. Effect of Data Division on TCPI Model Performance**

| Data Division % | | | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|---|
| Training | Testing | Querying | | | |
| 65 | 15 | 20 | 8.55 | 8.00 | 88.00 |
| 65 | 20 | 15 | 9.15 | 7.95 | 89.71 |
| 70 | 15 | 15 | 9.85 | 7.85 | 90.00 |
| 75 | 15 | 10 | 9.85 | 7.70 | 90.50 |
| 80 | 10 | 10 | 11.65 | 7.65 | 92.10 |
| 85 | 5 | 10 | 14.65 | 6.85 | 92.30 |
| 85 | 10 | 5 | 14.65 | 6.70 | 92.30 |

The best division is 85% for the training set, 10% testing set, and 5% for the validation set; therefore, the accuracy of this division was approved in the TCPI model basing on the minimum testing error (6.7%) and maximum coefficient of correlation (r) (92.30%). The impact of using various selections for divisions (i.e. blocked, striped, and random) was studied, and the results are illustrated in Table (17). The presentation of the TCPI model did not affect comparatively by changing the method of division. The using of blocked division shows a better presentation according to the adopted minimum testing error (6.7%) and the maximum coefficient of correlation (r) (92.30) as shown inTable 17.

**Table 17. Effects of Method of Division on TCPI Model Performance**

| Data division % | | | Choices of division | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|---|---|
| Training | Testing | Querying | | | | |
| 85 | 10 | 5 | blocked | 14.65 | 6.70 | 92.30 |
| 85 | 10 | 5 | striped | 12.50 | 8.65 | 90.00 |
| 85 | 10 | 5 | random | 15.5 | 10.5 | 85.88 |

#### 4.3.3. Model Architecture

The network of TCPI model is set to two hidden layers using the default variables of the software (learning rate equal to 0.2 and momentum term equal to 0.8 and the transfer functions in hidden and output layer node are sigmoid), many networks with various numbers of hidden layer nodes are developed, and the outcomes are listed in Table (18), since the highest no. of nodes equal to (2I+1) where (I) is the number of entered nodes. (i.e. maximum nodes equal to five). Marginal variances in testing errors values were noticed; thus, two hidden layers and one node for each layer were selected in this model that shows the minimum testing error (6.7%) and the highest coefficient of correlation (92.3%). It is supposed that the network with one hidden node is considered an optimal. Therefore, it was selected in this model.

**Table 18. Effects No. of Nodes on TCPI Model Performance**

| Model No. | No. of Nodes | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|
| 1 | 1 | 14.65 | 6.70 | 92.30 |
| 2 | 2 | 14.70 | 7.90 | 90.55 |
| 3 | 3 | 15.80 | 8.50 | 90.55 |
| 4 | 4 | 16.85 | 8.70 | 90.88 |
| 5 | 5 | 16.95 | 8.80 | 90.85 |

The impact of the momentum term on model performance was studied for the model with one hidden node (learning rate equal to 0.20). The outcomes are listed in Table 19. It could be noticed that the best value for momentum term is 0.9 that shows the minimum testing error (6.7%) and maximum coefficient of correlation (92.3%) as shown in Table 19; thus it was applied in this model.

**Table 19. Effect Momentum Term on TCPI Model Performance**

| Momentum Term | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|
| 0.10 | 15.95 | 7.90 | 90.00 |
| 0.20 | 15.85 | 7.80 | 90.30 |
| 0.30 | 15.85 | 7.80 | 91.40 |
| 0.40 | 15.75 | 7.70 | 91.50 |
| 0.50 | 15.75 | 7.60 | 91.60 |
| 0.60 | 15.73 | 7.50 | 91.60 |
| 0.70 | 15.72 | 7.20 | 91.65 |
| 0.80 | 15.70 | 6.90 | 91.65 |
| 0.90 | 14.65 | 6.70 | 92.30 |
| 0.95 | 14.65 | 6.60 | 93.00 |

Additionally, the impact of the learning rate on the model performance was investigated (momentum term = 0.9) for TCPI Model. The outcomes are listed in Table 2). The best value for learning rate is 0.2 that shows the minimum prediction error (6.7%) and the highest coefficient of correlation (92.3%) as shown in Table 18; thus it was applied in this model.

**Table 20. Effects Learning Rate on TCPI Model Performance**

| Learning Rate | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|
| 0.10 | 15.50 | 6.70 | 92.30 |
| 0.2 | 14.65 | 6.70 | 92.30 |
| 0.3 | 14.80 | 6.75 | 91.00 |
| 0.4 | 14.90 | 6.80 | 91.00 |
| 0.5 | 14.92 | 6.85 | 91.00 |
| 0.6 | 14.94 | 6.87 | 90.92 |
| 0.7 | 14.96 | 6.88 | 90.90 |
| 0.8 | 15.99 | 6.90 | 90.80 |
| 0.9 | 15.99 | 6.94 | 90.70 |
| 0.95 | 16.60 | 6.98 | 90.60 |

The impact of using various transfer functions (i.e. sigmoid and tanh) were studied. The results are illustrated in Table 21; the performance of the TCPI model did not affect comparatively by changing the kind of the transfer function. The best performance was attended when the sigmoid transfer function was used for hidden and output layers that shows the minimum prediction error of 6.7% along with the highest correlation coefficient (92.30%).

**Table 21. Effect of Transfer Function on TCPI Model Performance**

| Transfer function | | Training Error % | Testing Error % | Coefficient Correlation (r)% |
|---|---|---|---|---|
| Hidden Layer | Output Layer | | | |
| Sigmoid | Sigmoid | 14.65 | 6.70 | 92.30 |
| Sigmoid | Tanh | 15.65 | 7.70 | 92.00 |
| Tanh | Sigmoid | 15.65 | 8.75 | 91.50 |
| Tanh | Tanh | 15.65 | 8.75 | 90.00 |

#### 4.3.4. TCPI Model Equation

A limited number of connection weights were attended by Neuframe for the best formula TCPI model. It is enabling the network to be transformed into a moderately modest formula. The organization of the TCPI model is illustrated in Figure 5, also weights of connection and levels threshold (bias) are listed in Table 22.

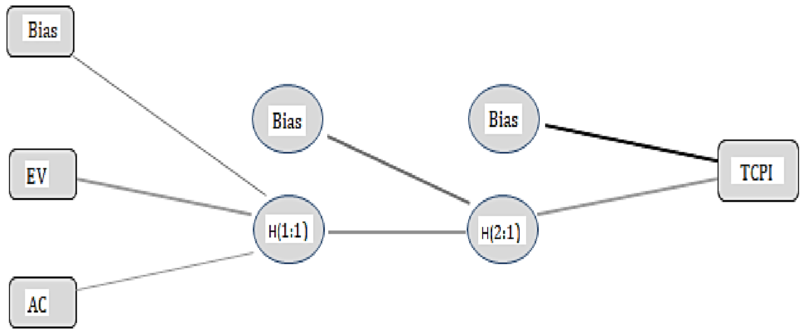


**Figure 5. Architecture of TCPI Model**

**Table 22. Weight and Threshold Levels for the TCPI Optimal**

| **Predictor** | | **Predicted** | | |
|---|---|---|---|---|
| | | **Hidden Layer 1** | **Hidden Layer 2** | **Output Layer** |
| | | **H(1:1)** | **H(2:1)** | **TCPI** |
| Input Layer | (Bias) | -.702 | | |
| | EV | -1.293 | | |
| | AC | 2.367 | | |
| Hidden Layer 1 | (Bias) | | -.537 | |
| | H(1:1) | | 2.693 | |
| Hidden Layer 2 | (Bias) | | | -19.079 |
| | H(2:1) | | | 27.642 |

By applying the connection weight and the threshold levels illustrated in Table 22, the prediction of the equation TCPI can be expressed as follow:

$$SPI = \frac{0.58}{1 + e^{[19.079 - 27.642 \times \tanh(x)]}} + 0.97 \quad (6)$$

$$X = [-0.702 + (2.367 \times 10 - 6 \times \mathrm{F2}) - (1.293 \times 10 - 6 \times \mathrm{F4})] \times 2.693 - 0.537 \quad (7)$$

Where F2: AC, Actual Cost, and F4 is EV, Earned Value.

A numerical example has been provided for a better understanding of the application of the formula. The equation was examined against the data used in the ANN model training (TCPI. Model). Where EV equal to 303616250 ID, a good agreement has been noticed between the estimated value using Equation 6 and measured value where they were 0.97 and 1.00796 respectively (case no.1). The difference is very little.

## 5. Verification and Validation of the Mathematical Models

The calculation of network performance is essential to assess models, and it can be done by calculating two values:

1) Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error is defined by the following equation:

$$\mathrm{MAPE} = \sum_{i=1}^{n} \left(\frac{\mathrm{A} - \mathrm{E}}{\mathrm{A}} \times 100\right)/2 \quad (8)$$

Where A is the actual values, E is the estimated values.

2) Average Accuracy (AA):

Accuracy performance is defined as (100−MAPE) %. Average Accuracy (AA) could be determined by the following equation:

$$AA\% = 100 - MAPE \ = \ 100 - 16.91 \ = \ 83.09\ \% \tag{9}$$

Where ANN equations are obtained by Neuframe V.4 program, and the comparison between the actual Performance Indexes that have been obtained from residential buildings project under construction.

## 6. Web-based Software Development to Predicting Earned Value Indexes

Using ANN for EV prediction in construction projects needs a modern, efficient control technique, which has extra advantages. As well as creating and developing a web-based application for this purpose through which the program is developed and evaluated, presented, and coded in user-friendly software using PHP-MySQL language. The software employs an Artificial Neural Network to perform the calculations of the Earned Value Indexes quickly, accurately, and without effort. The software is composed of two main parts: Creating sets and data and calculating forecasts as well as summarizing results by comparing them to actual data using the three methods SPI, CPI, and TCPI. The Web-Based Software consists of; User Interface, Historical Data, Adaptation module to re-optimize ANN models on new historical cases and accordingly adapt the model's performance to new environments. The operation of the developed Web-Based Software is represented by the overall flow chart.

### 6.1. Web-based Project Forecast Walkthrough

This web-based software consists of several steps firstly, connect to htt://salahalhemiary.com, enter the username and password, create a new set, and specify the number of projects to process N. Letter N is used to indicate the number of projects specified by the user. There is no limit to the number of projects that can be specified by the user, but a minimum of one project is required (although this is not feasible for the project forecast in this thesis), enter required parameters for N; BAC, AC, AP, EV, P%, PV, calculate the SPI, CPI, and TCPI, save to database and finally show results.

A user can log in using a simple username and password procedure and create by the administrator (registration and using the software free is the second stage of this software). After successful login, a user can create a new project set, preview, modify, and print previous sets. Upon creating a new set, it is required from the user to specify the number of projects to enter data then specifying data for any number of projects, firstly enter the BAC, then AC, AP, EV, and P%, and then enter the actual value of SPI, CPI, and TCPI. Any entered project data should have the following parameters (BAC, AC, AP, EV, P%, PV), which are essential for obtaining estimate SPI, CPI, and TCPI according to the proposed mathematical formulae presented earlier. Therefore, after specifying the project's data, the software calculates the required performance parameters (SPI, CPI, and TCPI) and compares it to the actual parameters with a summary. After click "Save", a summary can be viewed for the calculated data and predicted; also, Table 23 illustrated the value of AA% and MAPE% for the ANN technique.

**Table 23. Illustrated the value of AA% and MAPE% for ANN technique**

| # | BAC | AC | A% | EV | P% | PV | Data | Method | SPI | CPI | TCPI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | **Actual** | | 0.77778 | 0.98554 | 1.00796 |
| 1 | 867475000 | 308071875 | 35 | 303616250 | 45 | 390363750 | Forecast | NN | 0.78907 | 1.057 | 0.97 |
| | | | | | | | | | 1.00 | 0.77435 | 1.55318 |
| 2 | 867475000 | 616143750 | 55 | 477111250 | 55 | 477111250 | Forecast | NN | | | |
| | | | | | | | | | 0.73061 | 0.74246 | 0.970 |
| | | | | | | | | | 1.11111 | 0.8274 | 1.26359 |
| 3 | 867475000 | 524215625 | 50 | 433737500 | 45 | 390363750 | Forecast | NN | | | |
| | | | | | | | | | 1.249 | 0.84153 | 0.97030 |
| | | | | | | | | | 1.25 | 0.97151 | 1.00987 |
| 4 | 867475000 | 223228750 | 25 | 216868750 | 20 | 173495000 | Forecast | NN | | | |
| | | | | | | | | | 0.91426 | 0.74201 | 0.97 |

| NN | Model SPI | Model CPI | Model TCPI |
|---|---|---|---|
| MAPE | 16.91 % | 9.17% | 17.12% |
| AA% | 83.09% | 90.83% | 82.88% |

The proposed cost estimation program's evaluation program indicates that it is effective in estimating earned value indexes. Certain comments and notes have been raised about the applicability of the proposed managerial tool, which could be handled through efficient support at the decision-making levels and enhancing the users' computer skills. The results of web-based software were interpreted in terms of Average Accuracy (AA%) equal to 83.09, 90.83 and 82.88% for SPI, CPI, and TCPI, respectively, by ANN technique.

## 7. Conclusions

This research has studied the predicting the performance of residential buildings using the artificial neural network approach. The findings of this study are quite compelling and therefore it is possible to draw the following conclusions:

- In comparison with other methods, it has been noticed that the ANN method shows excellent outcomes of prediction.
- The outcomes were interpreted in terms of Average Accuracy (AA%) that equalled to 83.09, 90.83 and 82.88%, and MAPE that equalled to 16.91, 9.17 and 17.12, for SPI, CPI, and TCPI, respectively.
- The correlation coefficient (r) is equal to 90.95, 93.00 and 92.30% for SPI, CPI, and TCPI, respectively.
- It was found that the prediction model derived from the ANN technique indicated that there are a few variances between the theoretical and the practical results.
- The results of this investigation show that the MLR technique showed good results of estimation in terms of Average Accuracy Percentage (AA%) and correlation coefficient (R) generated by MLR model for SPI, CPI and TCPI, where the AA% were 95.89, 96.89 and 95.91% .and R were 92.911, 98.916 and 97.837% for SPI,CPI, and TCPI respectively.
- The results above are completely similar to the results obtained from models, which shows how accurate the web-based software is so it could be used to predict earned value indexes. This software can be used with a high, fast, excellent accuracy and with no effort to conclude the required forecasts.

## 8. Declarations

### 8.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.


### 8.2. Funding

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### 8.4. Conflicts of Interest

The authors declare no conflict of interest.

## 9. References


[1] Koster, K., D. Wallace, J. Kinder, and C. Bell. "Earned Value Management for Dummies, Deltek Special Edition." (2011).

[2] Lipke, Walt, Ofer Zwikael, Kym Henderson, and Frank Anbari. "Prediction of Project Outcome." International Journal of Project Management 27, no. 4 (May 2009): 400–407. doi:10.1016/j.ijproman.2008.02.009.

[3] Kadhum, Mohammed. "Prediction of Mechanical Properties of Reactive Powder Concrete by Using Artificial Neural Network and Regression Technique after the Exposure to Fire Flame." Jordan Journal of Civil Engineering 9, no. 3 (2015): 381-399.

[4] Pajares, Javier, and Adolfo López-Paredes. "An Extension of the EVM Analysis for Project Monitoring: The Cost Control Index and the Schedule Control Index." International Journal of Project Management 29, no. 5 (July 2011): 615–621. doi:10.1016/j.ijproman.2010.04.005.

[5] Leśniak, Agnieszka, and Michał Juszczyk. "Prediction of Site Overhead Costs with the Use of Artificial Neural Network Based Model." Archives of Civil and Mechanical Engineering 18, no. 3 (July 2018): 973–982. doi:10.1016/j.acme.2018.01.014.

[6] Moslemi Naeni, Leila, Shahram Shadrokh, and Amir Salehipour. "A Fuzzy Approach for the Earned Value Management." International Journal of Project Management 32, no. 4 (May 2014): 709–716. doi:10.1016/j.ijproman.2013.02.002.

[7] Zhong, Shuheng, and Xin Wang. "Improvement and Application of Earned Value Analysis in Coal Project Management." Procedia Engineering 26 (2011): 1983–1989. doi:10.1016/j.proeng.2011.11.2394.

[8] Vanhoucke, M, and S Vandevoorde. "A Simulation and Evaluation of Earned Value Metrics to Forecast the Project Duration." Journal of the Operational Research Society 58, no. 10 (October 2007): 1361–1374. doi:10.1057/palgrave.jors.2602296.

[9] Chen, Hong Long, Wei Tong Chen, and Ying Lien Lin. "Earned Value Project Management: Improving the Predictive Power of Planned Value." International Journal of Project Management 34, no. 1 (January 2016): 22–29. doi:10.1016/j.ijproman.2015.09.008.

[10] Modranský, Róbert, Kateřina Bočková, and Michal Hanák. "Project Manager and Stress in Coping with Demanding Situations in Automotive Industry." Emerging Science Journal 4, no. 5 (October 1, 2020): 418–426. doi:10.28991/esj-2020-01241.

[11] Kadhum, Mohammed Mansour, and Zaid Ahmed Mohammed. "Predict the Ultimate Moment Capacity of Reactive Powder Concrete Beams Exposed to Fire Flame Using Artificial Neural Network and Multiple Linear Regression Models." International Journal of Engineering and Technology 9 (2017): 2637-2649.

[12] Kim, Mansu, Sungwon Jung, and Joo-won Kang. "Artificial Neural Network-Based Residential Energy Consumption Prediction Models Considering Residential Building Information and User Features in South Korea." Sustainability 12, no. 1 (December 22, 2019): 109. doi:10.3390/su12010109.

[13] AL-Somaydaii, A. J., H. S. M. Aljumaily, and F. M. S. AL-Zwainy. "Utilization multifactor linear regression technique for prediction the earned value in bridges projects." Journal of Engineering and Applied Sciences 13, no. 7 (2018): 1676-13.

[14] Khamees, Shahad S., Mohammed M. Kadhum, and Nameer A. Alwash. "Effects of Steel Fibers Geometry on the Mechanical Properties of SIFCON Concrete." Civil Engineering Journal 6, no. 1 (January 1, 2020): 21–33. doi:10.28991/cej-2020-03091450.

[15] Omotayo, Temitope, Awuzie Bankole, and Ayokunle Olubunmi Olanipekun. "An Artificial Neural Network Approach to Predicting Most Applicable Post-Contract Cost Controlling Techniques in Construction Projects." Applied Sciences 10, no. 15 (July 28, 2020): 5171. doi:10.3390/app10155171.

[16] Alawadi, Sadi, David Mera, Manuel Fernández-Delgado, Fahed Alkhabbas, Carl Magnus Olsson, and Paul Davidsson. "A Comparison of Machine Learning Algorithms for Forecasting Indoor Temperature in Smart Buildings." Energy Systems (January 24, 2020). doi:10.1007/s12667-020-00376-x.

[17] M. Kadhum, Mohammed, Salah M. Harbi, Shahad S. Khamees, Mustafa S. Abdulraheem, and Ehsan Noroozinejad Farsangi. "Punching Shear Behavior of Flat Slabs Utilizing Reactive Powder Concrete with and Without Flexural Reinforcement." Practice Periodical on Structural Design and Construction 26, no. 1 (February 2021): 04020060. doi:10.1061/(asce)sc.1943-5576.0000551.