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Predicting Earned Value Indexes in Residential Complexes' Construction Projects Using Artificial Neural Network Model

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Abstract: Background: The back propagation neural network model as a smart technique can be used in this work proved to be very successful in modelling nonlinear at the same time and the interrelationships between them, and, it have the ability to predict the earned value indicators for residential Complexes buildings projects in Republic of Iraq, Objective: only one development intelligent forecasting model was presented to predict Schedule Performance Index (SPI), Cost Performance Index (CPI), and To Complete Cost Performance Indicator (TCPI) are defined as the dependent. Methodology: The approach is principally influenced by the determining numerous factors which effect on the earned value management, which involves Iraqi historical data. In addition, six independent variables (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) were arbitrarily designated and satisfactorily described for per construction project. Results: It was found that ANN has the capability to envisage the dust storm with a great accuracy. The correlation coefficient (R) has been 90.00%, and typical accuracy percentage has been 89.00%. Novelty: this study had found that the neural network models outperformed traditional linear methods and therefore they leave the great potential for replacing traditional methods in the area of earned value estimating and forecasting.

Keywords: Artificial neural network, Schedule performance index (SPI), Cost performance index (CPI), To complete cost performance indicator (TCPI), Predicting, Models.

1. Introduction

In early stage, a proper estimation is considered as a key factor of a construction project in accomplishment of any intended project. On the other hand, estimation is being a quite complex during the planning stage, while documentation besides drawings are not done yet. Thus, several techniques have been used to achieve a perfectly estimation in an early stage, while the information of the intended project is still restricted. [1]

Regarding the industry requirements, the performance measurement has an essential part in the process of the construction management. In which, the measurement of the performance gives the important data to evaluate factors for the owners of the project, contractors, and the management experts; that is to manage the progress of the construction, to make an estimate of the construction project cost for future. [2]

Different studies have used ANNs model in construction management. Mainly for the classification, making the decision, planning, optimization, and the predicting. William in 1993 promoted networks of back-propagation to estimate varies in the cost index of the construction [3]. Murtaza and Deborah in 1994 applied a neural network individually together with Khonen Algorithm for creating the decision on the modularization of the construction [4]. Hegazy and Moselhi in 1994 applied artificial neural network of back-propagation to obtain a best mark-up model of estimation, so that resulting in having solutions to new tender situations [5]. Lippmann in 1988 applied an ANN for modeling the rough cost calculations of construction [6]. Chua et al. in 1997 applied ANNs to point out main management factors which have an effect on budget activity in and project [7]. Al-Tabtabai et al. in 1997 applied a network of BP to obtain the decision-making process for the project professionals drawn in schedule monitoring and prediction for incomplete projects of multi-storey buildings [8]. Adeli and Wu in 1998 presented a regularization neural network to predict the reinforced concrete pavement cost [9]. Hegazy and Ayed in 1998 applied the neural network process to create a model of a parametric cost-estimating for projects of highway [10]. Al-Zwainy et al in 2015 used four neural networks for predicting the budget of highway under multiple criteria [11]. The researchers did not found any study that is exactly the same as the current study while searching in international libraries and discreet periodicals such as Scopus, Springer, Taylor France and others, as this current study is almost unique of its kind that deals with predicting the value indicators gained using neural networks, despite the existence of multiple studies dealing with a topic prediction in construction projects using neural networks, including the study of Zamim at el, 2019 [12] and the study of Ibrahim et al, 2018 [13].

Consequently, for the studies of the construction management, ANNs are now widely used. A significant gap has been noticed which that none of the above-mentioned studies was interested in earned value management predicting. In Iraq, some scholars have used ANNs in project management. Al-Zwainy. In 2009 presented four models related to the neural networks in order to predict the overall cost of construction thoroughfare projects in Iraq. [12]

Several names have employed for ANN: connectionist models, predicting models, parallel distributed processing models; forecasting systems; and artificial neural computing. ANN is considered as a part of artificial intelligence (AI) as such structures are depended on the system of the natural nervous. It may present an unbelievable number of the characteristics of human brain, such as; acquire a knowledge and simplified it from previous cases to new problems. Al-Zwainy and Aidan in 2017 found that when the processed data has errors or when the data is incomplete [13], ANN could present significant answers for it and it could process the information quickly when used to solve actual world issues. Neurocomputing architectures may be based on the physical hardware (machine or neurocomputer) or neurosoftware languages (or programs) which can behave just like human beings. The back-propagation network may consider as the most straightforward and realistic networks which applied in doing advanced tasks of human beings like: analysis, classification, making the decision, planning, and scheduling as compared with the different architectures and paradigms. Additionally, the modeling process of the neural network-based includes five important features: data acquisition, problem demonstration, and analyzing, architecture determination; understand the determination of the process; network training; and experimentation of the trained network to take a broad view of evaluation. [14]

One of the highly powerful and popular multilayer feed forward networks is trained with back-propagation. The training of the developed network is conducted by back-propagation algorithm which was developed and includes three stages of the feed forward of the input training patterns, the calculation and back-propagation stage of the associated error, and the adjustment stage of the weights [15-17].

The foremost goal of this paper is to construct artificial neural networks model to envisage the earned value indicators of residential buildings projects in Republic of Iraq. For achieving this, there is a necessity for identifying the factors that impact residential buildings projects performance. Consequently, the author in this paper is trying improvement of earned value model through the following steps:

1) Choose the appropriate neural networks Software.
2) Identification of ANNs models variables that have an effect on the earned value index in Iraqi residential buildings project.
3) Expansion and investigation of the proposed ANNs models to predict the earned value indexes.
4) Examine the substantiation and authentication of the developed mathematical models.

2. Choose the appropriate neural networks software

Today, neural networks are used for solving many business problems such as earned value forecasting. The researcher studied many neural network programs. The researcher found that the best program for neural networks, which is easy to use, and is compatible with all the problems simple and complex, and accepts all types of variables and different factors.

Numerous uses that provide for the statistics analysis establishment as in Microsoft Excel, STATISTICA, MINITAB, and MATLAB, however this paper adopts SPSS Program. SPSS stands for

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Table 1. Variables of ANN models

Parameters	Input					
	BAC	AC	A%	EV	P%	PV
MAX.	867475000	616143750	55%	477111250	60%	520485000
MIN.	867475000	223228750	25%	216868750	20%	173495000
AV.	867475000	392915000	30%	260242500	40%	346990000
RANGE	0.00	406500858	41%	353080781	45%	387410643
ST.D	0.00	94173338	8%	71577599	8%	66736932

	Output		
	SPI	CPI	TCPI
MAX.	1.2510	1.0573	1.5501
MIN.	0.7143	0.7420	0.9701
AV.	0.5358	0.3153	0.5801
RANGE	0.9101	0.8801	1.1301
ST.D	0.1201	0.0701	0.1101

Statistical Package for the Social Sciences for the premier statistics analysis environment. The SPSS simulator has visual, easy-to-use, object-oriented method for problem solving by means of intelligent technologies.

SPSS is used by numerous classes of investigators for multifaceted statistical data investigation. Long produced by SPSS Inc., it had been acquired by IBM in 2009. The up-to-date varieties have termed as IBM SPSS Statistics.

3. Identification ANN models variables

This study uses historic data analysis as the methodology foundation. Additionally, using historical data helps in giving a relation among the key factors influencing the earned value parameters of the residential buildings projects to create estimations for new projects.

ANN models necessitate lots of data. Consequently, many historic residential buildings projects were collected which had done between 2012 and 2016, in Mosel residential complex project in Iraq. The projects collected from cities, Ministry of Construction and Housing, consultants and contractors. Subsequently, the data has been analyzed. The used data and information collection method in this study is the direct and indirect data gathering from local engineering firms as a sub-contractor. Currently, a noteworthy obstacle interrupted this method due to the unsecured situation in Iraq, and the insufficiency in documentation. Despite of this difficulty, the scientists could gather a trusted and effectively data for more than fourty eight residential constructions projects. That was through coming some companies and introducing the intended documents and reports for residential buildings projects.

Moreover, these factors that effect on the earned value indexes adopted in Models of ANN as shown in the Table 1.

There are two types of variables that affected on the earned value in residential complex project in Republic of Iraq that are dependent variables and Independent variables.

3.1 Dependent variables

Cost Performance Index (CPI), Schedule Performance Index (SPI), and To Complete Cost Performance Indicator (TCPI) have been defined as the dependent variable and every specific engineering project has employed as the elementary unit of the observation.

3.2 Independent variables

After starting the dependent variables that projected via ANNs model, it has been essential for developing independent variables to clarify any variant in earned value indexes. There are many variables as an independent variable such as:

1) F1: BAC, Budget at Completion.
2) F2: AC, Actual Cost.
3) F3, A%, Actual Percentage.
4) F4: EV, Earned Value.
5) F5: P%, Planning Percentage.
6) F6: PV, Planning Value,

4. Development ANN models

Artificial Intelligent Neural Network (AINN) models must be in a methodical manner for improving its performance. Such method requirements address major factors like development of model inputs, data division and pre-processing, development of model architecture, model optimization (training), stopping standards, and model authentication. An organized approach for evolving the model was employed for solving the problem at hand. This approach has five main phases:

1) Model inputs and outputs
2) Data division
3) Model architecture
4) ANNs Model Equation
5) ANNs Model Validity

Mathematical models are divided into to three parts, the detailed description of these stages are concluded in the following section:

The specified variables at the stage of the data identification have been applied for developing the ANN models. Three mathematical models have established in this section, the features of the project in a mathematical model were applied to estimate earned value indexes. SPSS version 24 was used as a tool and technique to building the three models, as following:

1) Schedule Performance Index (SPI)
2) Cost Performance Index (CPI),
3) To Complete Cost Performance Indicator (TCPI).

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

4.1 Development of model inputs and outputs

Selected model input variables have the most important influence on the model performance as the significant step in evolving ANN models. Huge number of input variables for ANN models typically upsurges the network size, resultant in a reduction in processing speed and a decrease in the network efficiency. Different methods were recommended for selecting input variables such as Method of prior knowledge: based on prior knowledge, the suitable input variables can be chosen. This method is typically used in the field of project management, and is adopted in this study.

As an initial stage for neural network modeling, the problem at hand requires identifying and tagging the data as input or as output. SPSS v.24 has Microsoft Excel sheet, which is used through this step. The independent factors influencing the problem have recognized and measured as (N) input parameters, which are characterized by nodes at the input buffer of a neural network. The output of the model is Schedule Performance Index (SPI) and the input of this model is Earned Value (EV) and Planned Value (PV).

4.2 Data division ANN model

Data pre-processing has been highly important for employing neural nets positively. It evaluates what information is presented to produce a model throughout the training phase. Consequently, the subsequent step in the ANN model’s development has been isolating the existing data into three subsets, training, testing and validation sets. Learning has achieved on the training set, which is employed for estimating the weights while the cross-validation set has adopted for generalization for producing better output for unseen instances. Nevertheless, the test set is used for measuring the generalization ability of the network, and evaluated network performance.

In the current step of the ANN models development, the current data has divided into three sets of training, testing, and validation sets. The separation may be prepared by separating the data when they having bottommost testing error and the maximum coefficient correlation. This separation may be achieved by using Neuframe software. In this study, a specified network was used which has the best performance regarding the testing error (in order to compare to other standards to assess the prediction performance, training error and correlation of validation set). By applying the software parameters as it is, different networks with a number of divisions have been developed. The results are briefed in Table 2.

It could be noticed from the Table 2 that the finest part is 80% for training set, 10% testing set, and 10% for validation set, in relation to taken testing error and coefficient of correlation (r) 5.300% and 90.950% respectively. Therefore, this part was accepted in ANN model. The influence of using numerous choices for divisions (i.e. blocked, striped, and random) has considered and presented in Table 3. It can be said that the performance of ANN model was quite insensitive to the separation process. When the striped division was applied, the best performance was achieved.

4.3 Model architecture

One of the essential and tricky parts in the development of ANN models is to establish the model architecture. Usually, there is no direct and exact method to determine the proper number of nodes to include in every concealed layer. This issue becomes complex with increasing the number of hidden layers in the neural network.

Table 2. Effect of data division on ANN model behaviour

Data partition %			Error of Training %	Error of Testing %	Coefficient Correlation(r)%
Training set	Testing set	Querying set			
60	23	17	6.410	6.710	75.10
65	20	15	6.410	6.610	74.10
70	15	15	5.910	6.010	80.10
75	10	15	5.510	5.910	85.30
75	15	10	5.410	5.710	88.00
80	10	10	5.300	5.300	90.950
85	10	5	5.210	5.410	90.80
85	5	10	5.210	5.410	90.70

Table 3. Impacts of division method on the ANN model behaviour

Data partition %			Choices Division	Error of Training %	Error of Testing %	Coefficient Correlation(r)%
Training set	Testing set	Querying set				
80	10	10	Blocked	7.401	9.901	85.01
80	10	10	Striped	5.300	5.300	90.950
80	10	10	Random	6,501	7.701	88.01

Table 4. Influences the number of neuron on the ANN model performance

No. of Model	Effect of Parameters	Neuron No.	Error of Training %	Error of Testing %	Coefficient Correlation (r)%
1	Selections of striped division Learning Rate 0.2 Momentum Term 0.8 Transfer Function in hidden layer (Sigmoid) Transfer Function in output layer (Sigmoid)	1	5.300	5.300	90.095
2		2	5.410	5.910	90.191
3		3	5.910	6.510	87.451
4		4	6.310	6.810	86.871
5		5	6.781	6.901	85.621

The network of ANN Model has been adjusted to unique hidden layer through default parameters of the software (learning rate is 0.2 and momentum term is 0.8 and the transfer functions in hidden and output layer node are sigmoid). Many networks with various numbers of hidden layer nodes have been developed and the consequences have been depicted in Table 4, as the highest no. of nodes is (2I+1) in which (I) characterizes the number of input nodes. (i.e. maximum nodes equal to five).

As a result, only single hidden node has been selected in the present model with the lowermost testing error (5.300 %). It is supposed that the network with one hidden node has been considered optimal. Hence, it has designated in this model.

The influence of the momentum term on model outcomes has been studied for the model of one hidden node (learning rate equal to 0.20). The consequences have presented in Table 5. It could be noticed that the optimal value for momentum term has been (0.8) with minimum testing error of (5.30%), therefore it has been adopted in this model.

After that, the test errors start to decrease to

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Table 5. Influence the term of momentum on the ANN model outcomes

Effect of Parameters	Term of Momentum	Error of Training %	Error of Testing %	Coefficient Correlation (r)%
Model No. 1 Choices of division (striped)	0.10	7.710	8.310	80.310
Learning Rate	0.20	7.610	7.710	83.310
(0.2)	0.30	7.510	7.510	85.210
No. of Nodes (1)	0.40	6.310	6.610	87.410
Transfer function in hidden layer(Sigmoid)	0.50	6.310	6.410	87.910
	0.60	6.210	6.210	88.410
Transfer function in output layer (Sigmoid)	0.70	6.110	5.310	89.610
	0.80	5.300	5.300	90.950
	0.90	5.310	5.219	90.117
	0.95	5.310	5.218	90.110

Table 6. Influences the rate of learning on the ANN model performance

Effect of Parameters	Learning Rate	Error of Training %	Error of Testing %	Coefficient Correlation (r)%
Model No. 1 Choices of division (striped)	0.11	6.760	5.350	90.950
	0.20	5.300	5.300	90.950
Momentum Term (0.80)	0.31	6.340	5.930	90.010
	0.41	6.770	5.990	90.210
No. of Nodes (1)	0.51	6.980	6.200	90.080
	0.61	7.760	6.300	88.280
Transfer function in hidden layer(Sigmoid)	0.71	7.540	6.500	89.560
	0.81	8.440	6.800	87.850
Transfer function in output layer (Sigmoid)	0.91	8.490	6.900	85.560
	0.950	8.680	7.100	84.540

some extent within 0.8-0.95 range. So that the acquired optimal value for the momentum term has been (0.800) with training error of (5.300%) and significant minimum testing error (5.300 %) and the highest correlation coefficient (r) equal to (90.950 %). Therefore, it has been employed in this model.

Furthermore, the consequence of the learning rate on the model performance has been examined (momentum term equal to 0.80) for ANN Model. The consequences have presented in Table 6. The optimal value for Learning Rate (LR) has been (0.2) with minimum lowest prediction error of (5.3%); henceforth it has been employed in this model.

Therefore, the gotten optimal value for the Learning Rate (LR) equal to (0.200) with significant testing error, significant value training error and great significant coefficient of correlation (90.950 %); henceforth, it has been employed in this model.

The impacts of adopting dissimilar transfer functions (i.e. tanh and sigmoid) have been examined and as depicted by Table 7. Accordingly, ANNs model performance has been reasonably unresponsive to the kind of the transfer function. The finest performance has been predicted at what time the sigmoid transfer function has been employed for hidden and output layers with the

Table 7. Impact transfer functions in ANN model performance.

Effect of Parameters	Transfer Functions		Errors		Coefficient correlation (r)%
	Hidden Layer	Output Layer	Training %	Testing %	
Model No.1 Choices of division (striped) Momentum Term (0.8) Learning Rate (0.2) No. of Nodes (1)	sigmoid	sigmoid	5.300	5.300	90.950
	sigmoid	tanh	6.561	6.331	89.991
	tanh	sigmoid	6.551	6.261	85.391
	tanh	tanh	5.781	7.161	84.641

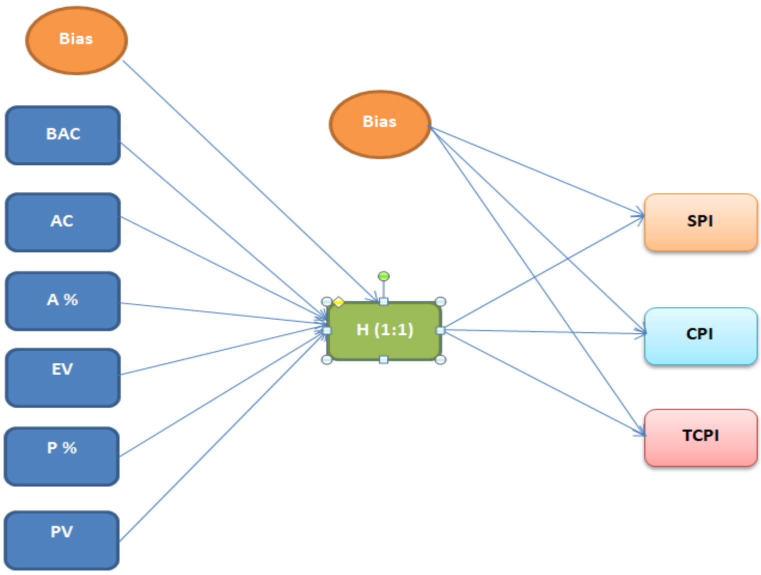

Figure. 1 Architecture of ANN model

Table 8. Weight and threshold levels for the SPI optimal

Predictor		Predicted			
		Hidden Layer 1	Output Layer		
		H(1:1)	SPI	CPI	TCPI
Input Layer	(Bias)	-.080			
	BAC	.035			
	AC	-2.446			
	A	.010			
	EV	1.271			
	P	-.127			
	PV	.537			
Hidden Layer 1	(Bias)		.735	-2.127	.885
	H(1:1)		-2.901	3.595	-4.482

smallest prediction error 5.300 % coupled with highest correlation coefficient (r) (90.950 %).

4.4 EVM indicators model equation

Minor connection weights have been gotten by SPSS for the optimum SPI, CPI and TCPI models. The neural network is converted into practically modest formulation. The group of ANN model has been exemplified in Fig. 1, although the weights of connection and levels threshold (bias) have been explained by Table 8.

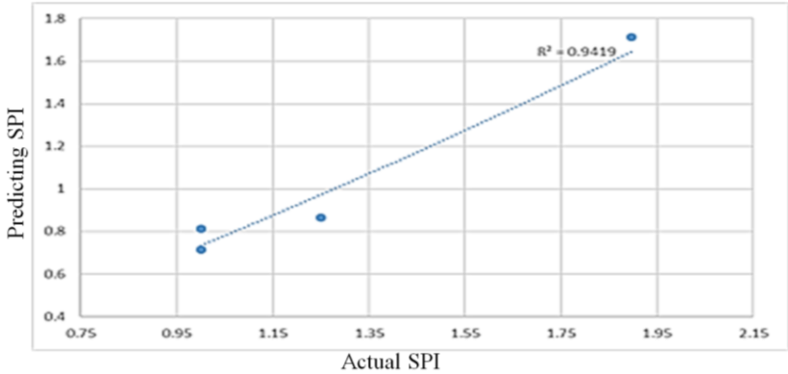

Figure. 2 Study the relationship between observed and predicted SPI for validation data

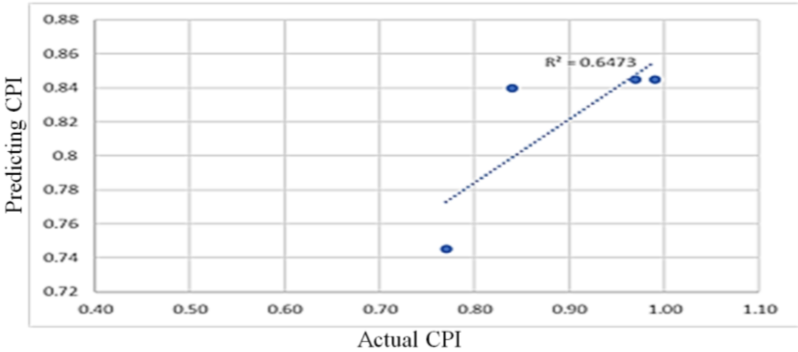

Figure. 3 Study the relationship between observed and predicted CPI for validation data

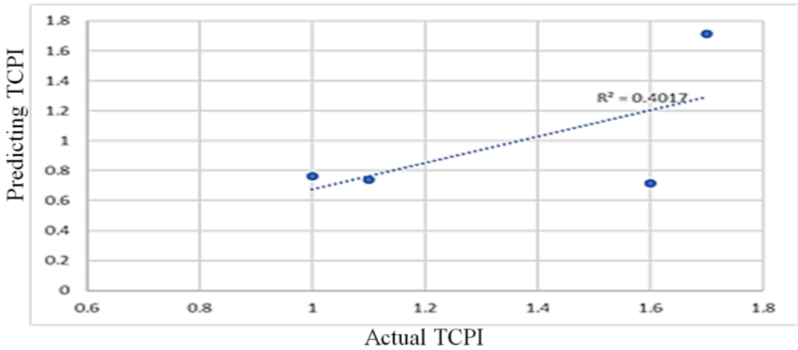

Figure. 4 Study the relationship between observed and predicted TCPI for validation

Based on connection weight besides the threshold levels presented in Table 8, the prediction of the SPI is written as:

SPI = {1\ [1+exponential (-0.735+2.901tanh (x))] +0.71401} (1)

CPI = {1 \ [1+exponential (2.127-3.595tanh(x))] +0.74201} (2)

TCPI = {1\ [1+exponential (-0.885+4.482tanh(x))] +0.9701} (3)

Where:

X=[-0.080+(0.035(BAC))+(-2.446(AC)) + 0.010(A%)+1.271(EV)+(-0.127(P%)+0.537(PV)]. (4)

5. Verification and validation of the ANN model

The summary of computing Cost Performance Index (CPI), Schedule Performance Index (SPI), and To Complete Cost Performance Indicator (TCPI) by ANN for verification of estimating models has explained by Table 9. Where column two has actual Index that gotten from residential buildings project under construction in Iraq, and column (3) represents estimate Index after applying ANN

Table 9. SPI, CPI and TCPI calculated through ANN for verification of estimating model

Projects	SPI		CPI		TCPI	
	Actual	Estimate by ANN	Actual	Estimate by ANN	Actual	Estimate by ANN
1	1.000	0.714	0.770	0.745	1.600	0.970
2	1.250	0.8653	0.970	0.845	1.000	1.02142
3	1.000	0.8143	0.840	0.84	1.100	0.995562
4	1.900	1.714	0.990	0.845	1.700	1.970
Correlation Coefficient	**98.03%**		**80.45%**		**63.38%**	

Table 10. Verification of ANN model

Project.	F1 BAC	F2 AC	F3 A%	F4 EV	F5 P%	F6 PV	SPI = EV / PV	CPI = EV / AC	TCPI = (BAC-EV)/(BAC-AC)
1	867.48	616	0.55	477	0.55	477	1.00	0.77	1.600
2	867.48	223	0.25	217	0.2	73	1.25	0.97	1.000
3	867.48	360	0.35	304	0.35	304	1.00	0.84	1.100
4	867.48	308	0.35	304	0.45	338	1.90	0.99	1.700

Table 11. (MAPE) of SPI

projects	Actual SPI	Estimate SPI by ANN	MAPE%
1	1.000	0.7140	28.600
2	1.250	0.8653	30.7769
3	1.000	0.8143	18.5739
4	1.900	1.7140	9.66757
MAPE%		**87.62/4=21.90**	

Table 12. (MAPE) of CPI

projects	Actual CPI	Estimate CPI by ANN	MAPE%
1	0.770	0.745	3.21266501
2	0.970	0.845	23.16881655
3	0.840	0.840	11.27827626
4	0.990	0.845	24.72096167
MAPE%		**62.38/4= 15.60**	

equation on them, where ANN equation has gotten through SPSS program. The comparison between the estimated and actual Index is shown.

Correlation coefficient between columns (Actual Index and Estimate Index by ANN equal to 98.03%, 80.45% and 63.38% for Schedule Performance Index (SPI), Cost Performance Index (CPI), and To Complete Cost Performance Indicator (TCPI) respectively, therefore it can be concluded that this model has an excellent covenant with the actual measured results, as presented in Figs. 2, 3, and 4.

The description of four observations of residential buildings project (variables) is shown in Table 10 below. The Performance Measures have been significant in evaluating models; there have been dual magnitudes used in measuring the network performance for a specific data set. [18]

a) Mean Absolute Percentage Error (MAPE)

Based on Boussabaiena in 1999, the mean absolute percentage error is defined by the following formula [19]:

$$\text{MAPE} = \{ \sum_{i=1}^{n} \frac{|A-E|}{A} \times 100\ \%\ \backslash n \} \qquad (5)$$

b) Average Accuracy (AA):

In conjunction with Wilmot and Mei, Accuracy performance has been described as (100−MAPE) %. Average Accuracy (AA) can be calculated by the following formula [20]:

Table 13. (MAPE) of TCPI

projects	Actual TCPI	Estimate TCPI by ANN	MAPE%
1	1.600	0.970	39.3750
2	1.000	1.02142	2.141995809
3	1.1000	0.995562	9.494394105
4	1.700	1.970	15.88235294
MAPE%		**66.89/4= 16.72**	

Table 14. Results of the Comparative Study

Description	ANN model SPI	ANN model CPI	ANN for model TCPI
MAPE	21.90%	15.60	16.72
AA%	78.10%	84.40	83.82
R	0.9303	0.8045	0.6338
R2	0.9419	0.6473	0.4017

$$AA\%=100-MAPE \quad (6)$$

The outputs of the comparative study have been specified in Table 14. The MAPE and average Accuracy percentage produced by ANN model (SPI) have been 21.90% and 78.10% correspondingly. Consequently, ANN model (SPI model) has a good conformity with the actual measured results; MAPE and AA% produced by ANN model (CPI) have been 15.60% and 84.40% respectively. Therefore, it can be concluded that ANN model (CPI model) shows a great conformity with the actual measurements, MAPE and AA% generated by ANN model (TCPI) have been 161.72% and 83.82% respectively. For that reason, ANN model (TCPI model) has great conformity with the actual measured results, finally, this study had found that the neural network models outperformed traditional linear methods such as multiple linear regressions and therefore they leave the great potential for replacing traditional methods in the area of earned value estimating and forecasting.

6. Conclusions

In this research the ANN technique was developed for the earned value analysis. The ANN system has been applied in order to develop new prediction model by using back propagation process by SPSS software. Historical data in this technique was used into three flocks, which are training, testing and validating. It has been noticed that the ANN technique shows excellent results of prediction. The consequences have been deduced based on Average Accuracy (AA %) equal to 78.10, 84.09, 84.40 and 83.82, also, correlation coefficient (R) equal to 93.03%, 80.45% and 63.38% for SPI, CPI and TCPI respectively. The model of estimation that derived by ANN technique pointed out that there are a few variations among the hypothetical and the applied consequences. As a result, ANN method stands for the finest choice for developing the prediction model since it has more correct earned value estimation. Finally, this study recommends conducting a future study to predict the Earned Value Indexes using Support Vector Machine technique, in order to compare results, and to review the technique more accurately.

The Availability of Data

The study findings which are supported by the data, are obtainable by the corresponding's writer upon requests.

Conflicts of Interest

The writers affirmed that they hadn't interest conflicts.

Acknowledgment

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Author Contributions

Faiq M. S. Al-Zwainy conceived of the presented idea and contributed to sample preparation and wrote the manuscript. Duaa Al-Jeznawi developed the ANN model and performed the computations. Ibraheem A. Aidan verified the analytical methods and supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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