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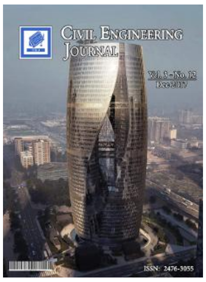

Modeling the Completion Time of Public School Building Projects Using Neural Networks

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Abstract

The Ministry of Education in Iraq is confronting a colossal deficiency in school buildings while stakeholders of government funded school buildings projects are experiencing the ill effects of extreme delays caused by many reasons. Those stakeholders are particularly worried to know ahead of time (at contract assignment) the expected completion time of any new school building project. As indicated by a previous research conducted by the authors, taking into account the opinions of Iraqi experts involved with government funded school building projects, nine major causes of delay in school building projects were affirmed through a questionnaire survey specifically are; the contractor's financial status, delay in interim payments, change orders, the contractor rank, work stoppages, the contract value, experience of the supervising engineers, the contract duration and delay penalty. In this research, two prediction models (A and B) were produced to help the concerned decision makers to foresee the expected completion time of typically designed school building projects having (12) and (18) classes separately. The ANN multi-layer feed forward with back-propagation algorithm was utilized to build up the mathematical equations. The created prediction equations demonstrated a high degree of average accuracy of (96.43%) and (96.79%) for schools having (12) and (18) classes, with (R^2) for both ANN models of (79.60%) and (85.30%) respectively. It was found that the most influential parameters of both models were the ratio of the sum of work stoppages to the contract duration, the ratio of contractor's financial status to the contract value, the ratio of delay penalty to the total value of contract and the ratio of mean interim payments duration to the contract duration.

Keywords: Construction Delay; Artificial Neural Networks; School Projects.

1. Introduction

Nowadays, all types of construction projects in Iraq are experiencing delay for some common causes like ill security, and other particular ones related to each project circumstances. A standout amongst the most imperative types of construction projects in Iraq is government funded school building projects. As indicated by the yearly statistics issued by the Ministry of Education, there are (2716) existing schools in Iraq till (2012). Around (1431) of them are utilized by more than one school with double or triple time of inhabitance (MOEDU) [1]. Furthermore, the Synopsis of National Development Plan (2013-2017) expressed that Iraq need to build (7220) kindergartens, (2250) primary schools and (791) secondary schools, keeping in mind the end goal to take care of the issue of double and triple time of inhabitance, replace mud schools and to take care of future demand because of the population natural growth which is around (3.3%) yearly (MOP) [2].

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All prevailing studies concentrates on variables happened at the time of construction that impact the completion time of projects with a specific end goal to keep away from them later on. The need in current Iraqi circumstance is to utilize the data accessible at contract assignment to foresee the expected completion time of construction projects, not the one expressed in the contract, keeping in mind the end goal to re-plan cash-flow and other resources requirements and to anticipate the expected occupation time. Government funded school building projects are incredibly in need of such a tool.

The Iraqi public school buildings sector is in a great need to predict the actual completion time of works. No attempts have been found to use the information available at the time of contract assignment to predict the expected completion time. Such predicted time can help the decision makers to maneuver with resources and to know in advance the expected date of using the facility.

The aim of this research is to develop a mathematical model that is capable to predict the expected completion time (ECT) of public school building projects at the time of contract assignment using ANN technique and to verify the most influential causes of delay through sensitivity analysis.

2. Research Methodology

This research is complementary to a previous research conducted by the authors where the most influential factors in predicting the completion time of public school building projects were found [3]. In this research the following steps were carried on:

- Historical data about the nine causes were obtained from the General Directorate of School Buildings then used to develop two ANN models for typically designed schools having (12) and (18) classes separately.
- Both models were statistically tested.
- Sensitivity analysis was carried out to find out the most influential causes.

3. Literature Review

Khaled, et al [3] determined the most common causes of delay in completing public school building projects in Iraq. A questionnaire form was distributed to owners, consultants, supervising engineers and contractors engaged in the public school buildings sector and the analyses of their opinions yielded nine most influential factors that cause delays. Those factors were: the contractor's financial status, the policy of interim payments, the history of change orders, the contractor ranking, the history of work stoppages, the contract value, the experience of supervising engineers, the contract duration and the delay penalty. Information about such factors is available at the time of contract assignment so can be used to estimate the completion time using a suitable model.

Bhokha and Ogunlana [4] created an artificial neural network to forecast the construction duration of buildings at the predesign stage. A three-layered back-propagation network consisting of 11 input nodes has been constructed. One real-value input for the functional area and ten binary input nodes for the basic information of the building features including; building function, structural system, foundation, height, exterior finishing, quality of interior decorating and accessibility to the site. The input nodes are fully connected to one output node through hidden nodes. Data of 136 buildings built during 1987-1995 in the Greater Bangkok area were used for training and testing the network. The best network was found to consist of six hidden nodes with a learning rate of 0.6 and null momentum having an average error of 13.6%. Attal [5] aimed at developing prediction models for highways projects construction duration and cost. It has been found that using ANN technique yielded higher accuracy and reliability than linear regression technique showing an (R) value of 85.75% and an average error of 0.0013. Yahia, et al [6] created a neural network to find a time contingency for construction projects through the study of the most important factors affecting time contingency in Egypt. It has been found that the average time contingency of the collected data was 28% and the most important factors affecting time contingency include; change orders, payment delays, delayed decision making, high percentage of critical activities, late project changes, missing project scope items, workload on the contractor resources, inaccurate control and follow up, unexpected requirements by client’s supervisor, deficiency of planning by the contractor, inadequate supply, bad quality and timing of information and drawings by the designer. Petruseva, et al. [7] created a neural network model for predicting construction project duration using data of 75 buildings constructed in the Federation of Bosnia and Herzegovina. He found that the multilayer perceptron neural network model indicates significant improvement in the accuracy of prediction. The model is found to have R^2 = 96.99% and MAPE = 2.50%.

Gab Allah [8] aimed at developing an artificial neural network model to predict the expected construction duration of building projects in its early stage. The validity of the model clearly showed that it has a good prediction capability with a maximum error of 14%.

4. Artificial Neural Networks

4.1. Definition of ANN

The ANN is a modeling technique that attempts to simulate human brain and nervous system. It learns by training using actual set of input variables and the corresponding outputs to determine rules that govern relationships between variables. It is well suited to model complex problems where the relationships between variables are unknown and non-linearity is suspected. The concept of artificial neurons was first introduced by McCulloch and Pitts, in 1943. Nevertheless, research in ANN applications has blossomed since the introduction of the back-propagation-training algorithm for feed -forward ANN in 1986. It may thus be considered a relatively new tool in the field of prediction and forecasting [9].

4.2. Structure and Operation of ANN

A typical structure of ANN consists of a number of artificial neurons known as processing elements, nodes or units that are usually arranged in layers: input layer, output layer and one or more intermediate layers called hidden layers as shown in Figure 1.

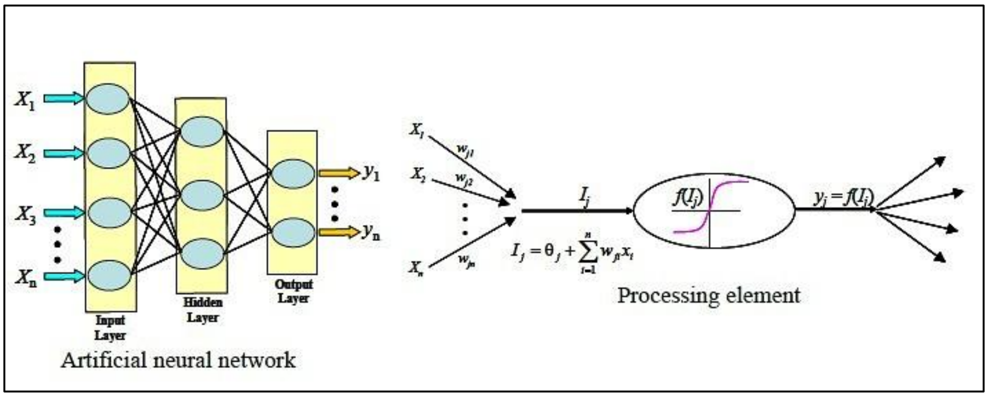

Figure 1. Structure and operation of ANNs [10]

Each processing element in a specific layer is fully or partially connected to many other processing elements via weighted connections. The scalar weights determine the strength of the connections between interconnected neurons. A zero weight refers to no connection between two neurons and a negative weight refers to a prohibitive relationship.

An individual processing element receives its weighted inputs from other processing elements, which are summed and a bias unit or threshold is added or subtracted. The bias unit is used to scale the input to a useful range to improve convergence properties. The result of this combined summation is passed through a transfer function (logistic sigmoid or hyperbolic tangent) to produce the output of the processing element. For node (j), this process is summarized in equations (1) and (2).

$$I_j = \sum W_{ji} X_i + \theta_j \tag{1}$$

$$Y_j = f(I_j) \tag{2}$$

Where:

I_j: the activation level of node (j).

W_{ji}: the connection weight between (j) and (i).

X_i: the input from node (i) for (i = 0, 1… n).

θ_j: the bias or threshold for node (j).

Y_j: the output of node (j).

$f(I_j)$: the transfer (activation) function.

The propagation of information starts at the input layer where the input data are presented. The network adjusts its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error. This process is called ‘learning’ or ‘training’. Once the training phase of the model has successfully been accomplished, the performance of the trained model has to be validated using an independent testing set [10].

4.3. Transfer (Activation) Functions

Transfer functions can take a variety of forms. The logistic sigmoid and hyperbolic tangent transfer functions are the most common functions in neural networks. The logistic sigmoid function is usually used when the desired range of output values is between 0 and 1 whereas the hyperbolic tangent function is often used when the desired range of output values is between -1 and 1. The logistic sigmoid transfer function is shown in Figure 2 and Equation 3. The hyperbolic tangent transfer function is shown in Figure 3 and Equation 4. Usually, the same transfer function is used for all processing elements in a particular layer [9].

$$\mathbf{f(I_j)} = \frac{\mathbf{1}}{\mathbf{1 + e^{-(I_j)}}} \tag{3}$$

$$\mathbf{f(I_j)} = \frac{\mathbf{e^{(I_j)} - e^{-(I_j)}}}{\mathbf{e^{(I_j)} + e^{-(I_j)}}} \tag{4}$$

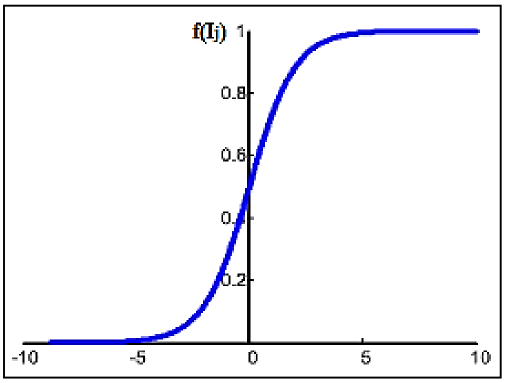

Figure 2. The logistic sigmoid function (Ipsic) [11]

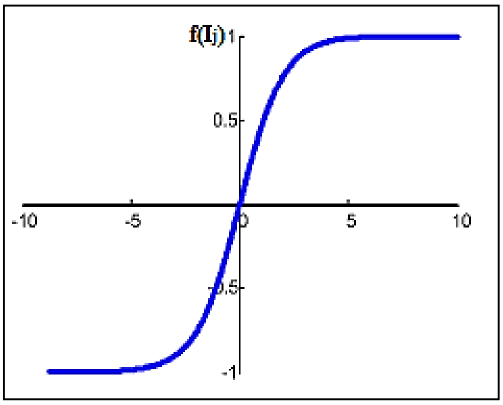

Figure 3. The hyperbolic tangent function(Ipsic) [11]

5. ANN Models Inputs

The data needed to develop the artificial neural networks models were obtained from (72) projects having (12) classes and (56) projects having (18) classes, all completed in the period (2004-2011). Information was extracted from the records of the General Directorate of School Buildings in the Ministry of Education. The projects were selected to be of the same design, number of stories, gross floor area, and procurement method. Prediction of the completion time was performed using neural networks for both types of projects. The factors that have the most significant impact on the completion time of public school building projects were treated in order to fit analysis requirements so they become as shown in (Table 1).

Table 1. Independent Objective Variables

	Variables codes and Description	Unit
I_1	The ratio of delay penalty to the total value of contract.	-
I_2	The ratio of contractor's financial status to the contract value.	-
I_3	The contract value.	log IQD
I_4	The contract duration.	log day
I_5	The ratio of mean interim payments duration to the contract duration.	-
I_6	The ratio of the sum of work stoppages to the contract duration.	-
I_7	The ratio of mean change orders duration to the contractor duration.	-
I_8	The experience of the supervising engineers.	year
I_9	The contractor rank.	-

5.1. Data Preparation

Data pre-processing is essential when using neural networks. It determines what information is presented to create the model during the training, validation and testing phases. It takes the form of data scaling, normalization and transformation [12]. Transforming input data into some known forms (e.g. Log., Ln or Exponential, etc.) may be helpful to improve the ANN performance. Therefore the natural logarithm was used to transform the contract value (I_3) and contractor duration (I_4) parameters. The available data were also divided into subsets in order to develop the ANN model. Subsets were checked using Neuframe 4 program to ensure the best data division. The default parameters of Neuframe 4 program which were applied are: linear activation function for input layer, tanh function for both hidden and output layers, learning rate value equal to 0.2 and momentum term value equal to 0.8. Based on the minimum error of the testing set, the coefficient of correlation (R) and coefficient of determination (R^2) the best data division into subsets was found to be as shown in Table 2.

Table 2. Best Data Division to Subsets

Model (A) for school having (12) classes				
Number of Schools and (%)			R%	R^2%
Training	Validation	Testing		
57 (80%)	11 (15%)	4 (5%)	90.06	81.10
Model (B) for schools having (18) classes				
Number of Schools and (%)			R%	R^2%
Training	Validation	Testing		
42 (75%)	11 (20%)	3 (5%)	90.20	81.40

In order to ensure that all variables receive equal attention during training, the input and output variables were pre-processed by scaling them to eliminate their dimension. Scaling has to be proportional to the limits of the transfer functions used in the hidden and output layers i.e. (-1.0 to 1.0) for tanh transfer function and (0.0 to 1.0) for sigmoid transfer function. As part of this method, for each variable (x) having minimum and maximum values of (x_{min}) and (x_{max}), the scaled value (x_n) was calculated using equation (5) (Mahmood and Aziz) [12]:

$$\text{Scaled value} = \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \qquad (5)$$

5.2. Statistical Tests of Data

Analysis of some statistical parameters was carried out in order to ensure that the data divided into training, testing and validation sets represents the same statistical population. These parameters were the mean, standard deviation, minimum value, maximum value and ranged as shown in Tables 3 and 4. Results indicated that the training, testing, and validation sets were generally statistically consistent. To examine how representative the training, testing and validation sets are with respect to each other, a t-test was also carried out. The null hypothesis of no difference in the means of each two data sets was checked by t-test. Test statistics were carried out to examine the null hypothesis with a level of significance equal to 0.05 which means that there is a confidence level of 95% that the training, testing and validation sets are statistically consistent. The results of the t-test are given in Tables 5 and 6.

Table 3. Input and output statistics for the developed ANN model (A)

Data set	**Statistical Parameters**	**Actual Input Variables**									**Actual Output**
		I_1	**I_2**	**Ln(I_3)**	**Ln(I_4)**	**I_5**	**I_6**	**I_7**	**I_8**	**I_9**	**LnECT**
Training n=57	Range	0.00014	0.4612	0.70754	0.4054	0.1298	0.2645	0.5125	14.0000	4.0000	1.6036
	Min.	0.00028	0.0366	19.7235	5.4806	0.0277	0.0104	0.0416	1.0000	1.0000	5.6204
	Max.	0.00042	0.4978	20.4310	5.8861	0.1575	0.2750	0.5541	15.0000	5.0000	7.2240
	Mean	0.00041	0.1670	20.0671	5.5042	0.0839	0.0820	0.2730	7.7719	3.6315	6.0875
	Std.	0.00002	0.1019	0.1956	0.0755	0.0365	0.0594	0.1359	3.9006	1.5426	0.4177
Testing n=4	Range	0.00009	0.1669	0.0468	0.2231	0.1125	0.0666	0.1933	6.0000	4.0000	0.8913
	Min.	0.00033	0.1343	20.1401	5.4806	0.0208	0.0333	0.1333	6.0000	1.0000	5.7071
	Max.	0.00042	0.3013	20.1869	5.7037	0.1333	0.1000	0.3266	12.0000	5.0000	6.5985
	Mean	0.00037	0.1987	20.1673	5.5922	0.0793	0.0588	0.2170	9.7500	3.7500	6.0763
	Std.	0.00005	0.0741	0.0196	0.1288	0.0468	0.0301	0.0886	2.6299	1.8929	0.3814
Validation n=11	Range	0.00000	0.4282	0.9211	0.0000	0.1250	0.0937	0.3750	14.0000	4.0000	0.9149
	Min.	0.00042	0.0849	19.5593	5.4806	0.0416	0.0260	0.1041	1.0000	1.0000	5.6970
	Max.	0.00042	0.5132	20.4804	5.4806	0.1666	0.1197	0.4791	15.0000	5.0000	6.6120
	Mean	0.00042	0.2154	20.0749	5.4806	0.1007	0.0698	0.2818	9.7272	4.1818	6.0878
	Std.	0.00000	0.1336	0.2520	0.0000	0.0494	0.0327	0.1169	4.2916	1.4709	0.3057

- Model (A) concerns school buildings having 12 classes.

- Actual Output: Actual delay time from records.

Table 4. Input and output statistics for the developed ANN model (B)

Data set	Statistical Parameters	Actual Input Variables I_1	I_2	$Ln(I_3)$	$Ln(I_4)$	I_5	I_6	I_7	I_8	I_9	Actual Output LnECT
Training n=42	Range	0.00013	0.4773	0.7462	0.4054	0.1570	0.4437	0.4791	14.0000	4.0000	1.8055
	Min.	0.00027	0.0482	20.0007	5.4806	0.0246	0.0104	0.0416	1.0000	1.0000	5.6240
	Max.	0.00041	0.5255	20.7470	5.8861	0.1816	0.4541	0.5208	15.0000	5.0000	7.4295
	Mean	0.00040	0.1898	20.3766	5.5096	0.1023	0.0982	0.2142	8.5714	3.7380	6.0623
	Std.	0.00003	0.1246	0.2315	0.1056	0.0475	0.1116	0.1154	4.3959	1.2109	0.4685
Testing n=3	Range	0.00000	0.2955	0.4572	0.0000	0.0554	0.1593	0.1541	5.0000	2.0000	0.9452
	Min.	0.00041	0.2004	20.0760	5.4806	0.1167	0.0364	0.1458	10.0000	2.0000	5.7037
	Max.	0.00041	0.4960	20.5332	5.4806	0.1721	0.1958	0.3000	15.0000	4.0000	6.6489
	Mean	0.00041	0.3114	20.3474	5.4806	0.1418	0.0965	0.2250	12.0000	3.0000	6.1002
	Std.	0.00000	0.1609	0.2403	0.0000	0.0280	0.0866	0.0771	2.6457	1.0000	0.4906
Validation n=11	Range	0.00000	0.4086	0.5513	0.0000	0.1621	0.1239	0.1916	15.0000	3.0000	0.9748
	Min.	0.00041	0.0772	20.1557	5.4806	0.0228	0.0302	0.1208	1.0000	2.0000	5.6869
	Max.	0.00041	0.4858	20.7070	5.4806	0.1850	0.1541	0.3125	16.0000	5.0000	6.6618
	Mean	0.00041	0.2410	20.4075	5.4806	0.0900	0.0786	0.2390	7.2727	4.0909	6.1118
	Std.	0.00000	0.1259	0.2085	0.0000	0.0526	0.0411	0.0652	4.8392	0.9438	0.3933

- Model (B) concerns school buildings having 18 classes.

Table 5. Test of hypothesis for the developed ANN model (A)

Statistical parameters	Input Variables I_1	I_2	$Ln(I_3)$	$Ln(I_4)$	I_5	I_6	I_7	I_8	I_9	Actual Output LnECT
Data set	**Testing**									
t-value	1.367	-0.607	-3.616	-1.349	0.238	0.767	0.808	-0.994	-0.147	0.052
Lower critical value	0.000	-0.136	-0.156	-0.290	-0.034	-0.037	-0.083	-5.959	-1.735	-0.419
Upper critical value	0.000	0.073	-0.045	0.114	0.043	0.084	0.195	2.003	1.499	0.442
Sig.(2-tailed)	0.262	0.546	0.001	0.266	0.813	0.446	0.422	0.324	0.884	0.959
Results	Accept	Accept	Reject	Accept	Accept	Accept	Accept	Accept	Accept	Accept
Data set	**Validation**									
t-value	-2.423	-1.368	-0.116	2.361	-1.320	0.654	-0.199	-1.498	-1.091	-0.003
Lower critical value	0.000	-0.119	-0.143	0.004	-0.042	-0.025	-0.096	-4.561	-1.558	-0.265
Upper critical value	0.000	0.022	0.127	0.044	0.009	0.049	0.079	0.650	0.457	0.264
Sig.(2-tailed)	0.019	0.176	0.908	0.022	0.191	0.515	0.843	0.139	0.279	0.998
Results	Reject	Accept	Accept	Reject	Accept	Accept	Accept	Accept	Accept	Accept

- Model (A) concerns school buildings having 12 classes.
- Actual Output: Actual delay time from records.

Table 6. Test of hypothesis for the developed ANN model (B)*

Statistical parameters	Input Variables I_1	I_2	$Ln(I_3)$	$Ln(I_4)$	I_5	I_6	I_7	I_8	I_9	Actual Output LnECT
Data set	**Testing**									
t-value	-0.470	-1.607	0.211	0.470	-1.409	0.026	-0.158	-1.325	1.028	-0.135
Lower critical value	0.000	-0.274	-0.250	-0.095	-0.096	-0.132	-0.148	-8.647	-0.710	-0.604
Upper critical value	0.000	0.031	0.309	0.153	0.017	0.135	0.127	1.790	2.187	0.528
Sig.(2-tailed)	0.641	0.115	0.834	0.641	0.166	0.979	0.875	0.192	0.310	0.893
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
Data set	**Validation**									
t-value	-0.902	-1.210	-0.401	0.902	0.747	0.568	-0.681	0.855	-0.895	-0.321
Lower critical value	0.000	-0.136	-0.185	-0.035	-0.021	-0.050	-0.098	-1.752	-1.144	-0.359
Upper critical value	0.000	0.034	0.124	0.093	0.045	0.089	0.048	4.349	0.438	0.260
Sig.(2-tailed)	0.371	0.232	0.690	0.371	0.458	0.573	0.499	0.397	0.375	0.749
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept

- Model (B) concerns school buildings having 18 classes.

6. Developing the ANN Models

Where a network with one hidden layer can approximate any continuous function, provided that sufficient connection weights are used [13], one hidden layer was used to develop both models (A) and (B). The procedure adopted to find the optimal network architecture and the internal parameters that control the training process started with a number of trials that were carried out using the default parameters of the Neuframe 4 software with one hidden layer of one hidden node. The number of nodes was slightly increased until no significant improvement in the model performance was gained. According to Joarder [14], the network that performs best with respect to the lowest testing and training errors with high correlation coefficient of validation was retrained with different combinations of momentum terms, learning rates and transfer functions in order to improve the model performance. Consequently, the model that has the optimum momentum term, learning rate and transfer function was retrained a number of times with different initial weights until no further improvement occurred. Using the default parameters of the Neuframe 4 software which has a learning rate of 0.2, momentum term of 0.8, and a tanh transfer function in the hidden and output layers nodes, a number of networks with different numbers of hidden nodes were developed. For model (A), the network with one hidden node is found to have the lowest prediction error of 0.77% for the testing set with a high coefficient of correlation (R) of 90.06% and coefficient of determination (R^2) of 81.10%. On the other hand the model (B), the network with two hidden nodes is found to have the lowest prediction error of 2.97% for the testing set with a high coefficient of correlation (R) of 90.20% and coefficient of determination (R^2) of 81.40%.

The effects of the internal parameters that control the back-propagation algorithm on the performance of models (A) and (B) were investigated. The optimum values of the momentum term and the learning rate of model (A) are found to be 0.6 and 0.2 respectively, having a testing error of 0.60%, training error of 7.44%, maximum coefficient of correlation (R) of 89.2% and coefficient of determination (R^2) of 79.60%. The optimum values of the momentum term and the learning rate of model (B) are found to be 0.8 and 0.3 respectively, having a testing error of 2.91%, training error of 6.55%, maximum coefficient of correlation (R) of 92.40% and coefficient of determination (R^2) of 85.30%.

The effects of using different transfer functions (sigmoid vs. tanh) were also investigated for both models. For model (A), the better performance was obtained when the tanh transfer function was used for both hidden and output layers. A neural network of nine input neurons, one hidden layer neuron and one output is found to be the optimum architecture for this model as shown in Figure 4. For model (B), the better performance was obtained when the tanh transfer function was used for both hidden and output layers. A neural network of nine input neurons, two hidden layer neurons and one output is found to be the optimum architecture for this model as shown in Figure 5.

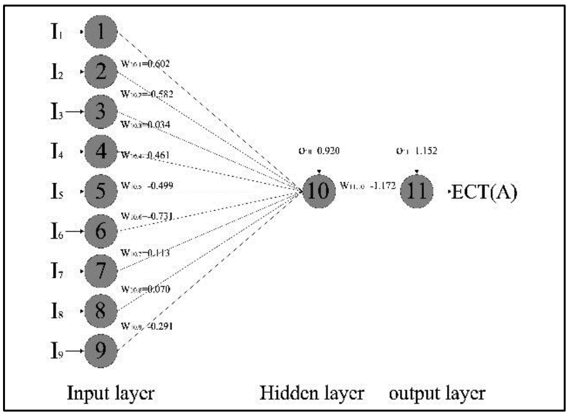

Figure 4. ANN model (A) optimal structure

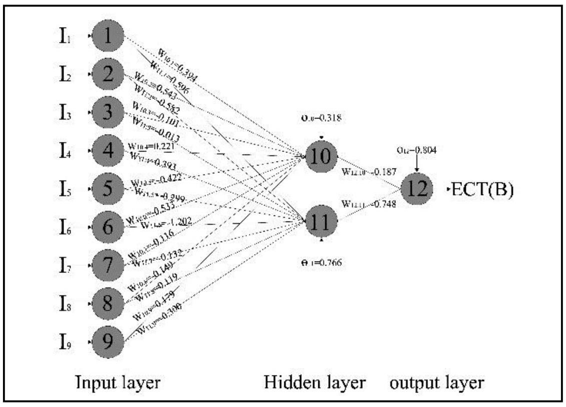

Figure 5. ANN model (B) optimal structure

6.1. Model (A) Final Equation

Using the connection weights and the threshold levels shown in Table 7 below, the predicted project completion time of public school buildings having 12 classes can be expressed as follows:

$$ECT(A)=InvLn[\frac{e^{(1.152-1.172tanhx1)}-e^{-(1.152-1.172tanhx1)}}{e^{(1.152-1.172tanhx1)}+e^{-(1.152-1.172tanhx1)}}] \quad (6)$$

Where:

$$x_1=\{\theta_{10}+(w_{10.1}*I_1)-(w_{10.2}*I_2)+(w_{10.3}*I_3)+(w_{10.4}*I_4)-(w_{10.5}*I_5)-(w_{10.6}*I_6)+(w_{10.7}*I_7)+(w_{10.8}*I_8)-(w_{10.9}*I_9)\} \quad (7)$$

Table 7. Connection weights and threshold levels for model (A)

Hidden layer nodes	w_{ij}: weight from node (i) in the input layer to node (j) in the hidden layer									Hidden layer threshold
	i = 1	i = 2	i = 3	i = 4	i = 5	i = 6	i =7	i = 8	i = 9	θ_j
j = 10	0.602	-0.582	0.034	0.461	-0.499	-0.731	0.113	0.070	-0.291	0.920
Output layer nodes	w_{ji}: weight from node (j) in the hidden layer to node (i) in the output layer									Output layer threshold
	i = 10									θ_j
j = 11	-1.172									1.152

It should be noted before using Equations 6 and 7, that all variables I_1 to I_9 must be converted to values between 0 - 1 because Equations 6 and 7 were built on this basis using Equation 5. In order to get actual data out of normalized ones, conversion to actual values were made using Equation 8 and Tables 3 and 7.

$$w_{actual} = \frac{w_{norm}}{I_{range}} \quad (8)$$

Where:

w_{norm}: Normalized weight of input variable data from Table 7.

I_{range}: Range of input training data from Table 3.

For the sake of scaling and substituting the weights and threshold levels, equations (6) & (7) can be rewritten as shown in Equations 9 and 10.

$$ECT(A)=InvLn[\frac{e^{(1.152-1.172tanhx1)}-e^{-(1.152-1.172tanhx1)}}{e^{(1.152-1.172tanhx1)}+e^{-(1.152-1.172tanhx1)}}\times range + min] \quad (9)$$

$$ECT(A)=InvLn[\frac{e^{(1.152-1.172tanhx1)}-e^{-(1.152-1.172tanhx1)}}{e^{(1.152-1.172tanhx1)}+e^{-(1.152-1.172tanhx1)}}\times 1.6036+5.5204] \quad (10)$$

Where:

$$x_1=\{-7.2231+(4300*I_1)-(1.2617*I_2)+(0.0481*I_3)+(1.1370*I_4)-(3.8434*I_5)-(2.7628*I_6)+(0.2205*I_7)+(0.0050*I_8)-(0.0728*I_9)\} \quad (11)$$

6.2. Model (B) Final Equation

Using the connection weights and the threshold levels shown in Table 8, the predicted project completion time of public school buildings having 18 classes can be expressed as shown in Equations 12 to 14.

$$ECT(B)=InvLn[\frac{e^{(0.804-0.187tanhx1-0.748tanhx2)}-e^{-(0.804-0.187tanhx1-0.748tanhx2)}}{e^{(0.804-0.187tanhx1-0.748tanhx2)}+e^{-(0.804-0.187tanhx1-0.748tanhx2)}}] \quad (12)$$

Where:

$$x_1=\{\theta_{10}+(w_{10.1}*I_1)+(w_{10.2}*I_2)-(w_{10.3}*I_3)+(w_{10.4}*I_4)-(w_{10.5}*I_5)-(w_{10.6}*I_6)-(w_{10.7}*I_7)-(w_{10.8}*I_8)+(w_{10.9}*I_9)\} \quad (13)$$

$$x_2=\{\theta_{11}+(w_{11.1}*I_1)-(w_{11.2}*I_2)-(w_{11.3}*I_3)+(w_{11.4}*I_4)-(w_{11.5}*I_5)-(w_{11.6}*I_6)-(w_{11.7}*I_7)+(w_{11.8}*I_8)-(w_{11.9}*I_9)\} \quad (14)$$

Table 8. Connection weights and threshold levels for model (B)

Hidden layer nodes	w_{ij}: weight from node (i) in the input layer to node (j) in the hidden layer									Hidden layer threshold
	i = 1	i = 2	i = 3	i = 4	i = 5	i = 6	i = 7	i = 8	i = 9	θ_j
j = 10	0.394	0.543	-0.101	0.221	-0.422	-0.533	-0.116	-0.149	0.179	0.318
j = 11	0.596	-0.538	-0.013	0.393	-0.299	-1.202	-0.132	0.119	-0.300	0.766
Output layer nodes	w_{ji}: weight from node (j) in the hidden layer to node (i) in the output layer									Output layer threshold
	i = 10	i = 11								θ_j
j = 12	-0.187	-0.748								0.804

It should also be noted that before using Equations 10, 13 and 14, all variables I_1 to I_9 must be converted as in model (A). In order to get actual data out of normalized ones, data were converted to actual values using Equation 8 and Tables 8 and 4.

For the sake of scaling and substituting the weights and threshold levels Equations 11, 12 and 13 can be rewritten as shown in Equations 15 to 18.

$$ECT(B)=InvLn\left[\frac{e^{(0.804-0.187\tanh x1-0.748\tanh x2)}-e^{-(0.804-0.187\tanh x1-0.748\tanh x2)}}{e^{(0.804-0.187\tanh x1-0.748\tanh x2)}+e^{-(0.804-0.187\tanh x1-0.748\tanh x2)}}\times range + min\right] \quad (15)$$

$$ECT(B)=InvLn\left[\frac{e^{(0.804-0.187\tanh x1-0.748\tanh x2)}-e^{-(0.804-0.187\tanh x1-0.748\tanh x2)}}{e^{(0.804-0.187\tanh x1-0.748\tanh x2)}+e^{-(0.804-0.187\tanh x1-0.748\tanh x2)}}\times 1.8055+5.6240\right] \quad (16)$$

Where:

$$x_1 = \{6.7862 + (2840.2700{*}I_1) + (1.1383{*}I_2) - (0.1348{*}I_3) + (0.5458{*}I_4) - (2.6878{*}I_5) - (1.2001{*}I_6) - (0.2427{*}I_7) - (0.0106{*}I_8) + (0.0448{*}I_9)\} \quad (17)$$

$$x_2 = \{-0.3751 + (4291.4754{*}I_1) - (1.1274{*}I_2) - (0.0179{*}I_3) + (0.9682{*}I_4) - (1.9033{*}I_5) - (2.7090{*}I_6) - (0.2756{*}I_7) + (0.0085{*}I_8) - (0.0751{*}I_9)\} \quad (18)$$

7. Sensitivity Analyses

To identify which of the input variables has the most significant impact on the project completion time (ECT), sensitivity analyses was carried out on both ANN models. According to Al-Janabi [15], a simple and innovative technique called Garson's algorithm (GA) was used to interpret the relative importance of the input variables by examining the connection weights of the trained network.

The sensitivity analysis results of model (A), shown in Table 9, indicates that (I_6: the ratio of work stoppages to the contract duration) has the most significant effect on the predicted project completion time of public school buildings having 12 classes with a relative importance of 21.60%. The other variables that have significant impact are (I_1: the ratio of delay penalty to the total value of contract), (I_2: the ratio of contractor's financial status to the contract value), (I_5: the ratio of mean interim payments duration to the contract duration) and (I_4: the contract duration), which showed relative importance values equals to 17.80%, 17.20%, 14.70% and 13.60% respectively. The sensitivity analysis results also indicates that (I_9: the contractor rank) have less impact on the predicted output with a relative importance of (8.60%), while (I_7: the ratio of mean change orders duration to the contractor duration), (I_8: the experience of the supervising engineers) and (I_3: the contract value) have a very low impact on the predicted output with relative importance values of 3.30%, 2.10%, and 1.00% respectively.

The sensitivity analysis results of model (B), shown in Table 10, indicates that (I_6: the ratio of work stoppages to the contract duration), as in model (A), has the most significant effect on the predicted project completion time of public school buildings having 18 classes with a relative importance of 26.75%. The other variables that have significant impact are (I_2: the ratio of contractor's financial status to the contract value), (I_1: the ratio of delay penalty to the total value of contract) and (I_5: the ratio of mean interim payments duration to the contract duration) which showed relative importance values equals to 17.71%, 15.72% and 12.10% respectively. The sensitivity analysis results also indicates that, (I_4: the contract duration) and (I9: the contractor rank) have less impact on the predicted output with relative importance values of 9.63% and 7.55% respectively, while (I_8: the experience of the supervising engineers), (I_7: the ratio of mean change orders duration to the contractor duration) and (I_3: the contract value) have a very low impact on the predicted output with relative importance values of 4.46%, 4.03% and 2.08%.

Table 9. Relative importance of each input in model (A)

Relative Importance (%)	I_1	I_2	$Ln(I_3)$	$Ln(I_4)$	I_5	I_6	I_7	I_8	I_9
	17.80	17.20	1.00	13.60	14.70	21.60	3.30	2.10	8.60
Rank	2	3	9	5	4	1	7	8	6

- Model (A) concerns school buildings having 12 classes.

Table 10. Relative importance of each input in model (B)

	I_1	I_2	$Ln(I_3)$	$Ln(I_4)$	I_5	I_6	I_7	I_8	I_9
Relative Importance (%)	15.72	17.71	2.08	9.63	12.10	26.75	4.03	4.46	7.55
Rank	3	2	9	5	4	1	8	7	6

- Model (B) concerns school buildings having 18 classes.

8. Models Evaluation

According to Khaled, et al [16], the statistical measures shown in Tables 11 and 12 were used to measure the performance of both prediction models. Results related to models (A) and (B) are also shown in both tables respectively.

Table 11. Model (A) performance measures

Description	Statistics
MPE	-3.27%
RMSE	0.244
MAPE	3.57%
AA%	96.43%
R	89.20%
R^2	79.60%

Table 12. Model (B) performance measures

Description	Statistics
MPE	-1.24%
RMSE	0.209
MAPE	3.21%
AA%	96.79%
R	92.40%
R^2	85.30%

The MAPE and percentage RMSE as measures of the average error are applied only to the independent test data. The MAPE and Average Accuracy Percentage generated by model (A) are found to be (3.57%) and (96.43%) respectively. On the other hand, the MAPE and Average Accuracy Percentage generated by model (B) are found to be (3.21%) and (96.79%) respectively. It is clear that both models overestimate the expected completion time of the projects by (90.91%) and (63.64%) using equation (10) for school having (12) classes and equation (16) for school having (18) classes respectively. Therefore it can be concluded that both model show a very good agreement with the actual observations. As a final step, the coefficient of determination was used to assess the validity of the derived equations of both ANN models. The natural logarithm (Ln) of the predicted values of the expected completion time of public school building projects (ECT) was plotted against the natural logarithm (Ln) of the observed (actual) values of the validation data set as shown in (Figures 6) and (7). It is clear from these Figures that there is a generalization capability in both ANN models in the domain of this type of data, for the coefficient of determination (R^2) is found to be (79.60%) for model (A) and (85.30%) for model (B). Therefore it can be concluded that these two models show a good agreement with actual observations.

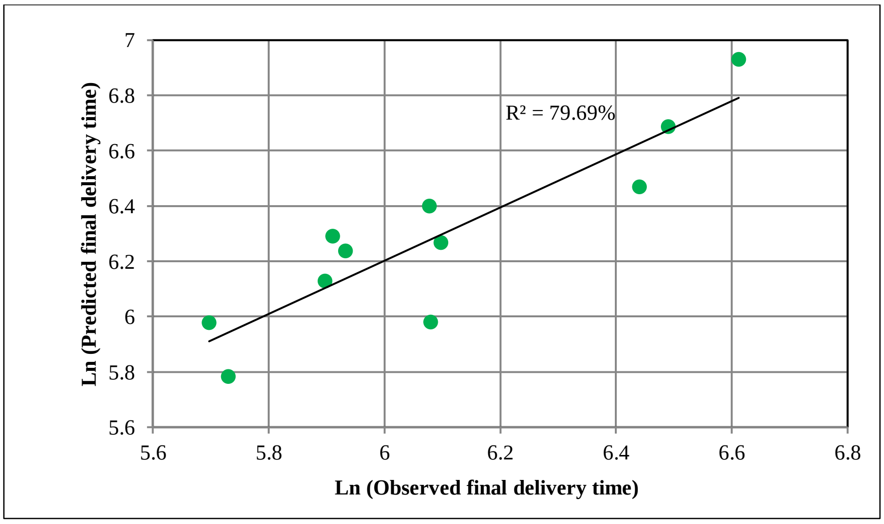

Figure 6. Observed vs. Predicted delivery time using ANN model (A) for school buildings having (12) classes

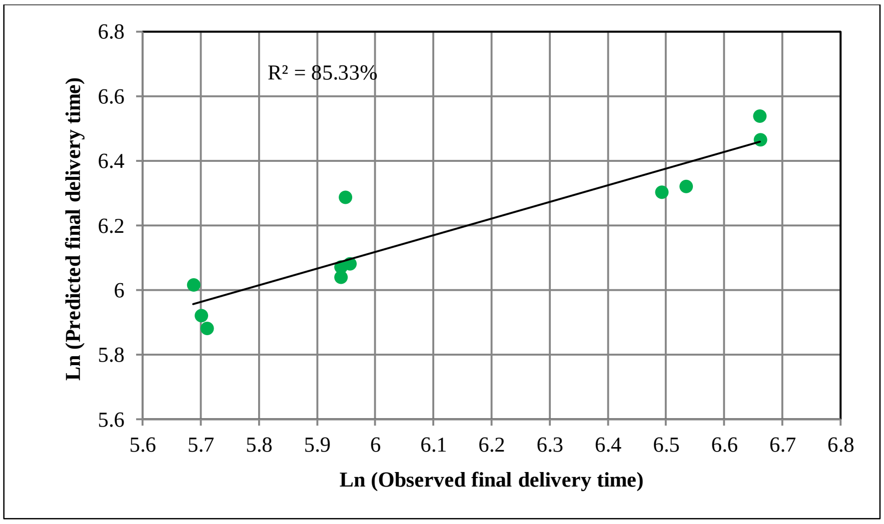

Figure 7. Observed vs. Predicted delivery time using ANN model (B) for school buildings having 18 classes

9. Conclusions

As a result of this research, the following conclusions are drawn:

- The nine most influential causes of delay according to the previous research [3] proved to be so using artificial neural networks. These causes are: the contractor's financial status, delayed interim payments, change orders, the contractor ranking, work stoppages, the contract value, the experience of supervising engineers, the contract duration and delayed interim payments.
- The historical data of 72 school projects having 12 classes and 56 school projects having 18 classes, all constructed in the period 2004-2011, concerning these nine causes was fair enough to develop two artificial neural networks models to predict the final completion time of public school building projects before the work starts.
- The validity and generalization of both models were met using the statistical validation measures of (MPE, RMSE, MAPE, AA and R^2). The (R^2) for ANN models (A) and (B) were 79.60% and 85.30% respectively.
- The developed models showed an excellent performance so can be generalized in Iraq to predict the final delivery time of public school building projects of the types having 12 and 18 classes.

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