



Using of an Artificial Neural Networks with Particle Swarm Optimization (ANN-PSO) Model in Prediction of Cost and Delay in Construction Projects

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ABSTRACT

Construction project delay is a global phenomenon. The delay risk being regarded as a main challenge that is tackled via the firms of construction. It possessed an inverse effect upon the performance of the project resulting in cost overruns and productivity reduction. In Iraq, most construction projects surpassed their prearranged time and were delayed, resulting in a loss of productivity and income. The objective of this paper was to predict the cost and delay of construction projects to illustrate their risks effects by using of artificial neural networks with the particle swarm optimization method (ANN-PSO). Thereby, risk factors were identified and analysed using Probability and Impact Analysis which were embraced as the model inputs. In comparison, the outputs for the models were represented by the ratio of the contractor's profit to project costs and the delay in construction projects. An ANN model was additionally evolved with a backpropagation (BP) optimization method to assess the exhibition of the ANN-PSO model. To evaluate the accuracy of the results of the ANN-PSO model, coefficient of correlation (R), determination coefficient (R²), and root mean squared error (RMSE) was utilized as performance evaluation of the models. The ANN-PSO model showed a significant performance in the delay prediction. The performance evaluation for the cost and delay prediction were (R=0.929, R²=0.863, RMSE=0.044), and (R=0.998, R²=0.996, RMSE=0.094), respectively. The model of ANN-PSO has a virtuous performance in the delay prediction better than the cost. However, the ANN-BP model showed better performance than ANN-PSO in term of cost prediction.

1. Introduction

The accurate estimation of construction costs in a construction project is a critical factor in the project's success. The estimation is done with minimum project information, which is helpful in the preliminary design stage [1]. It is more helpful for project managers to finish the work at a time and control the project is more effective [1]. Bakhary et al., 2015 [2] identified factors that contribute to cost overrun and potential measures to overcome the problem with the focus given to construction projects. Questionnaires were distributed to 30

respondents from construction firms. Descriptive statistics and ranking analysis were used in data analysis. The result showed that the most severe factor contributed to cost overrun was the inaccurate or poor estimation of the original cost. The essential method to control construction costs was proper project costing and financing. Ali et al, 2016 [3] identified the risk and cost management in the construction projects' variation management. A questionnaire as an instrument was utilized for collecting the data. Arbitrary sampling methods were employed for collecting the information, and

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(105) questionnaires were spread, and (90) were reverted. The correlation analysis showed an important relation among risk, cost, and variation management.

Alashwal and Chew, 2017 [4] distributed a questionnaire for collecting information from (83) administration agencies, consultant companies, and contractor for determining the use of simulation methods for the cost assessment and governing and for assessing their effect upon the cost-effectiveness of the project. The results manifested that the understanding of respondents and the use of the methods of cost simulation in construction manufacturing was slight.

Lee et al. 2019 [5] proposed a knowledge-based risk mapping tool for systematically estimating the risk-related parameters causing cost overrun in the global marketplaces.

Construction delays affected the time and cost of projects. A construction project is usually considered successful if it is completed on time, within its budget, and successfully achieves its quality targets [6]. Emam et al. 2015 [7] employed a wide variety of analytical methods to conclude the most precise statistical ranking of delay causes. A survey questionnaire was prepared and was subject to pilot interviews before issuing it to practitioners, including clients, consultants, and contractor organizations. Results revealed that the top five factors causing delay to large building projects are: slow decision-making; discrepancies between specifications and drawings, major changes in design during construction; delay in settlement of contractor claims; and unreasonable project time frames. Alotaibi et al., 2014 [8] examined the critical factors contributing to the construction delays and identified potential contributions of project management tools and techniques to minimizing them. Al-Kharashi and Skitmore (2019) [9] studied the causes of delays in public sector construction projects. They classified the causes of delay into six main groups: client-related causes; Contractor-related causes; consultant-related causes; Materials-related causes; Labour and equipment-related causes.

Artificial intelligence (AI) models have demonstrated their capability for solving the dynamic, uncertain, and intricate responsibilities [10]. Chou et al., 2013 [11] developed two ANN models to predict the lowest tender price of primary and secondary school buildings. The findings showed that the two ANN models effectively learned during the training stage and gained good generalization capabilities in the testing session with average accuracy percentages of 79.3% and 82.2%.

The Ministry of Municipal and Rural Affairs in Baghdad declared that most of the construction projects in Iraq surpassed their planned time and were delayed because the contractor cannot get concerned with the other projects. The efficient bidding system condition with the minimum tender price is lost; this is an important reason resulting in a deprived performance and delays in the public construction projects in Iraq [12].

Previous studies have focused on the causes of the cost's estimation [1-5] and construction delays [6-9]. However, previous studies did not predict the cost and delay using the Artificial neural network and particle swarm optimization. Thus, the objective of this study was to predict the cost and delay of construction projects by using the artificial neural networks with the particle swarm optimization method (ANN-PSO).

2. Methodology

The research methodology adopted in this study is summarized into the following steps:

1. Data collection: The required data on construction projects were collected from 47 construction projects from AL-ZAWRAA state company in Baghdad city.
2. Based on the collected data, two models were developed to predict the cost and delay in the construction projects using artificial neural network and particle swarm optimization.
3. Evaluating the performance of the two models adopted in this study was done using coefficient of correlation (R), determination coefficient (R²), and root mean squared error (RMSE).

3. The tools used for the model development

The tools adopted for developing the models for predicting the cost and delay in the construction projects are explained below:

3.1 Artificial Neural Networks (ANNs)

ANNs are insight devices enlivened by the natural neural organizations of people and creatures, which can advantageously learn designs and foresee the aftereffects of an issue in high-dimensional space [13]. They can plan a bunch of contributions to a bunch of yields in a

boisterous and complex dataset. Multi-layer perceptron (M.L.P.) is a solid and direct class of feed-forward ANNs. An ordinary M.L.P. network consists of the input layer, one or few hidden layers, and the output layer [14]. The first layer takes the worth of information sources and sends them to the accessible neurons in the second layer. Inside every neuron, a weighted amount of data sources is determined, and this worth in addition to a worth of inclination is changed by an enactment work, as demonstrated in Figure 1. At last, the yield signal is moved to the neurons in the output layer.

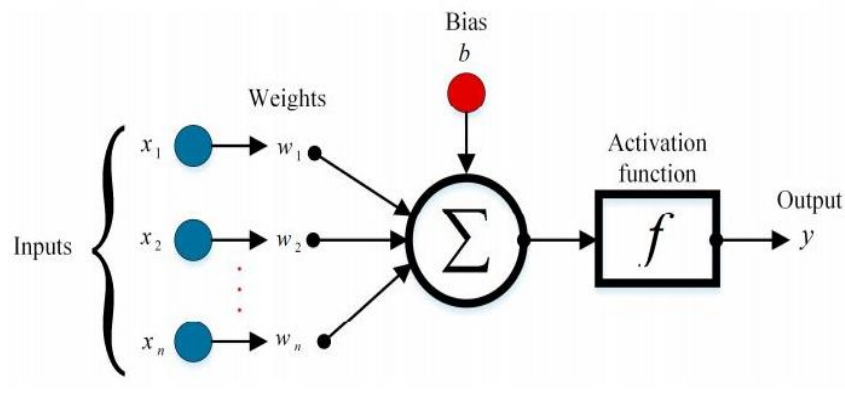


Figure 1. A process of neuron in the neural network

The mathematical process of ANN used in this study was formulated as below [15]:

$$I_j = \sum w_{ij}x_i + \theta_j \quad (1)$$

$$y_j = f(I_j) \quad (2)$$

Where:

I_j = activation level of unit j .

w_{ij} = the weight that binds between unit i and j .

x_i = the value of input of units.

θ_j = bias for unit j .

y_j = value of output for unit j .

$f(I_j)$ = transfer function.

The most common transfer function used in neural networks is the hyperbolic tangent and logistic sigmoid. As the problem of prediction is nonlinear so that the hyperbolic tangent has been used. It might prompt more exact results [16]. This function was somewhere in the range of -1 and 1 and is characterized as follows:

$$F(x_j) = \frac{e^{(x_j)} + e^{-(x_j)}}{e^{(x_j)} + e^{-(x_j)}} \quad (3)$$

Neural networks were trained to show expectable performance. Training is the process of changing and adjusting the weight of networks. The main object of this process is producing the weights between neurons which establish the total smallest error [17]. Backpropagation (BP) is the most optimization function used to train the neural network [9]. The Levenberg–Marquardt algorithm (L.M.A.) is regularly the quickest BP method in order to train the network [11]; so that a multi-layer perceptron (M.L.P.) neural network with the hyperbolic tangent activation function training by (B.P.) and (L.M.A.) optimization algorithm was used in this study.

3.2 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a developmental knowledge calculation that was motivated by the social conduct of bird rushing

or fish tutoring. Kennedy and Eberhart right off the bat proposed the PSO procedure in 1997 [16]. This calculation profits by a high velocity union rate among satisfactorily in many designing issues [18]. In this technique, an expense work that ought to be limited or expanded is at first characterized. At that point, many particles are made and disseminated in the D dimensional space of the issue. Every molecule contains the factors of the issue so that the objective function can be determined for every molecule. At last, every molecule's speed and position until the calculation meets [19].

$$V_i^{k+1} = w v_i^k + \frac{c_1 r_1 (P_{best,i}^k - P_i^k)}{\Delta t} + \frac{c_2 r_2 (G_{best}^k - P_i^k)}{\Delta t} \quad (4)$$

$$P_i^{k+1} = P_i^k + V_i^{k+1} \cdot \Delta t \quad (5)$$

where the addendums i and k mean the molecule and the cycle number, separately. $p_i = \{p_{i1}, p_{i2}, p_{ij}, \dots, p_{iD}\}$ and $V_i = \{v_{i1}, v_{i2}, \dots, v_{ij}, \dots, v_{iD}\}$ are the position and speed vectors, individually. The vectors $P_{k\ best,i} = \{p_{i1}, p_{i2}, \dots, p_{ij}, \dots, p_{iD}\}$ and $G_{k\ best} = \{g_1, g_2, \dots, g_D\}$ are the awesome position of the i th molecule over its set of experiences up to cycle k , and the situation of the best molecule in the multitude in emphasis k , individually. $I = 1, 2, 3, N$ is a counter to the quantity of particles, and D is the quantity of issue measurements or factors. Moreover, $C1$ is a psychological boundary showing the level of nearby inquiry, though $C2$ is a social boundary to mirror the worldwide pursuit level. Additionally, $r1$ and $r2$ are two free irregular numbers consistently appropriated somewhere in the range of 0 and 1, and w is the inertial weight used to save the past speed of the particles during the streamlining cycle. Δt is the time stretch in which the position and speed are refreshed; this boundary is normally viewed as equivalent to 1.

4. Models development

Models Development steps for predicting the cost and delay in the construction projects are listed accordingly.

4.1 Data and preparation

The data were used to make prediction models using (ANN-PSO) model. There were 47 construction projects gathered from AL-ZAWRAA state company in Baghdad city, a public sector company in which an engineering cadre is available for various engineering specialties such as civil, mechanics, and electricity. The required data related to construction projects were collected, and the period of its establishment ranges between (2010-2020). After that, this data was used to study the research's main problems: studying the cost of construction projects, which represented the percentage of the contractor's profit to the total cost of projects. In addition, 21 projects of 47 were considered to study the delay in the construction projects. Ten variables were selected to study cost and delay as inputs for the model. The output for the model was represented by the contractor's profit percentage concerning the total cost of the project concerning the cost and the delay period for the project about the project delay. As the prediction problem is nonlinear for this purpose, the input and output data are normalized in the interval between 0 and 1. To obtain a high accuracy of the model, the Interpolation Code was used. By trial and error, the researcher used 500 points to get better results. The top ten risk factors which has been concerned in this study can be summarized in table (1) and (2).

4.2. Performance evaluation

To evaluate the performance of the models, the coefficient of correlation (R), determination coefficient (R^2), and root mean squared error (RMSE) were utilized as performance evaluation of the models. These evaluation indicators can be utilized as below:

$$R = \frac{S(\sum_{k=1}^s T_k * P_k) - (\sum_{k=1}^s T_k)(\sum_{k=1}^s P_k)}{\sqrt{(s \sum_{k=1}^s T_k^2) - (\sum_{k=1}^s T_k)^2} * \sqrt{(s \sum_{k=1}^s P_k^2) - (\sum_{k=1}^s P_k)^2}} \quad (6)$$

$$R^2 = \frac{[\sum_{k=1}^s (T_k - \bar{T}_k) * (P_k - \bar{P}_k)]^2}{\sum_{k=1}^s (T_k - \bar{T}_k)^2 * \sum_{k=1}^s (P_k - \bar{P}_k)^2} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^s (P_k - \bar{P}_k)^2}{s}} \quad (8)$$

Where:
 P: measured output.
 T: actual output.
 S: total number of samples (training or testing)

model were 70% and 30%, respectively, and all the codes needed for building the models were developed in MATLAB program. The input and output data for ANN-BP and ANN-PSO models can be utilized in Tables 3 and 4.

It is essential to demonstrate that the percentage of training and testing for each

Table 1: Shows the top ten risk factors which have been selected for this study (output=cost)

Group	Factors
1- Owner	DF1: Financial problems. DF2: Slowness in making decisions. DF3: Delay in progress payments.
2- Contractor	DF4: Poor site management DF5: Delay in delivery of materials to site DF6: Construction mistakes and defective work.
3-Consultants	DF7: Design changes by the consultants DF8: Incomplete documents
4-External	DF9: Official and non-official holidays DF10: Lack of materials on market

Table 2: Show the top ten delay factors which have been selected for this study (output=delay)

Risk category	Type of risk
1-Natural risks	RF1: weather RF2: Fire
2-Political and environmental	RF3: War and Civil Disorder RF4: Changes in laws and Regulations
3-Financial & Economic	RF5: Inflation RF6: Financial Default of Subcontractor
4-Design	RF7: Inadequate Specifications RF8: Changes in design
5- Management and contract	RF9: Contract risks RF10: Business and Market risks

Table 3: Input and output data for (ANN, ANN-PSO) techniques (output=cost)

Projects	Inputs										Outputs
	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	
P1	0.0119	0.0004	0.0178	0.0007	0.0711	0.6640	0.1067	0.0030	0.0178	0.1067	0.2481
P2	0.0301	0.0004	0.0215	0.0009	0.6457	0.0861	0.0861	0.0430	0.0430	0.0430	0.2500
P3	0.0648	0.0003	0.0486	0.0019	0.0486	0.6479	0.0972	0.0097	0.0486	0.0324	0.3246
P4	0.0075	0.0015	0.0298	0.0009	0.0895	0.5965	0.1193	0.0060	0.0895	0.0596	0.3345
P5	0.0374	0.0007	0.0561	0.0015	0.1121	0.4484	0.1868	0.0075	0.1121	0.0374	0.1608
P6	0.0224	0.0008	0.0842	0.0006	0.0701	0.7013	0.0842	0.0084	0.0140	0.0140	0.2500
P7	0.0535	0.0002	0.0238	0.0029	0.2141	0.3569	0.1071	0.0036	0.2141	0.0238	0.1212
P8	0.0063	0.0003	0.0125	0.0005	0.1251	0.3752	0.3002	0.0050	0.1001	0.0750	0.1389
P9	0.0064	0.0003	0.0258	0.0010	0.1031	0.3866	0.1160	0.0258	0.3093	0.0258	0.3538
P10	0.0149	0.0006	0.0149	0.0003	0.1193	0.3579	0.0596	0.0447	0.3579	0.0298	0.0797
P11	0.0241	0.0002	0.0120	0.0002	0.0723	0.4817	0.0723	0.0120	0.2890	0.0361	0.1117
P12	0.0075	0.0003	0.0149	0.0006	0.1118	0.4474	0.2684	0.0149	0.0895	0.0447	0.1540
P13	0.0273	0.0016	0.0273	0.0033	0.2187	0.2460	0.2187	0.0109	0.2187	0.0273	0.4882
P14	0.0073	0.0009	0.0436	0.0006	0.0872	0.4360	0.1308	0.0029	0.1744	0.1163	0.1463

To be continued

P15	0.0048	0.0004	0.0096	0.0006	0.1533	0.4598	0.1149	0.0077	0.2299	0.0192	0.3333
P16	0.0478	0.0010	0.0358	0.0010	0.2149	0.2865	0.2149	0.0072	0.1433	0.0478	0.3344
P17	0.0842	0.0006	0.0421	0.0006	0.1122	0.5051	0.1684	0.0028	0.0561	0.0281	0.3333
P18	0.0404	0.0005	0.0505	0.0005	0.2018	0.3027	0.2270	0.0505	0.0505	0.0757	0.4215
P19	0.0228	0.0005	0.0512	0.0014	0.1024	0.4780	0.0683	0.0023	0.2049	0.0683	0.2500
P20	0.0277	0.0008	0.0593	0.0004	0.1187	0.5934	0.0396	0.0020	0.1187	0.0396	0.3334
P21	0.0030	0.0004	0.0119	0.0004	0.0714	0.3331	0.4996	0.0357	0.0357	0.0089	0.0528
P22	0.0126	0.0008	0.0113	0.0005	0.2270	0.3026	0.4035	0.0038	0.0252	0.0126	0.2431
P23	0.0894	0.0022	0.0894	0.0027	0.2683	0.4025	0.0447	0.0112	0.0224	0.0671	0.4329
P24	0.1531	0.0010	0.0510	0.0015	0.4592	0.2041	0.0510	0.0153	0.0255	0.0383	0.4314
P25	0.0504	0.0017	0.0336	0.0013	0.2518	0.3021	0.3021	0.0067	0.0168	0.0336	0.3793
P26	0.0806	0.0001	0.0101	0.0016	0.1209	0.6717	0.0806	0.0008	0.0134	0.0202	0.4218
P27	0.0101	0.0002	0.0051	0.0003	0.0911	0.5668	0.2530	0.0025	0.0607	0.0101	0.1129
P28	0.0960	0.0005	0.0180	0.0014	0.3599	0.1200	0.1080	0.0024	0.0060	0.2879	0.4231
P29	0.0322	0.0002	0.0048	0.0004	0.1934	0.3224	0.3869	0.0016	0.0484	0.0097	0.0007
P30	0.0276	0.0006	0.0061	0.0012	0.0983	0.6880	0.0491	0.0491	0.0737	0.0061	0.0526
P31	0.2517	0.0003	0.0060	0.0018	0.0599	0.3836	0.0360	0.0420	0.2158	0.0030	0.1299
P32	0.0123	0.0010	0.0247	0.0005	0.1972	0.2959	0.1972	0.0986	0.0986	0.0740	0.2738
P33	0.0801	0.0008	0.0200	0.0024	0.0801	0.2402	0.3603	0.0160	0.1601	0.0400	0.2606
P34	0.0449	0.0002	0.0056	0.0002	0.1348	0.3369	0.1348	0.0056	0.3145	0.0225	0.2850
P35	0.0231	0.0002	0.0347	0.0002	0.0924	0.6933	0.0924	0.0058	0.0231	0.0347	0.4244
P36	0.0214	0.0001	0.0053	0.0002	0.2139	0.4812	0.0962	0.0026	0.1711	0.0080	0.2500
P37	0.0206	0.0004	0.0103	0.0004	0.0411	0.7401	0.0822	0.0021	0.0411	0.0617	0.1122
P38	0.0082	0.0005	0.0163	0.0013	0.4081	0.0653	0.3265	0.0024	0.1632	0.0082	0.1113
P39	0.0803	0.0048	0.0535	0.0011	0.1606	0.6424	0.0268	0.0016	0.0021	0.0268	0.2509
P40	0.0467	0.0009	0.0156	0.0009	0.0622	0.7776	0.0622	0.0016	0.0012	0.0311	0.4286
P41	0.1588	0.0008	0.0212	0.0006	0.1906	0.4235	0.1906	0.0011	0.0021	0.0106	0.3333
P42	0.3813	0.0025	0.0508	0.0061	0.1525	0.1525	0.1525	0.0254	0.0254	0.0508	0.3571
P43	0.0024	0.0002	0.0095	0.0002	0.0851	0.2269	0.0851	0.5104	0.0756	0.0047	0.3341
P44	0.0599	0.0004	0.0200	0.0012	0.0599	0.5990	0.0799	0.0100	0.1597	0.0100	0.1231
P45	0.0531	0.0028	0.2125	0.0028	0.1416	0.4426	0.0708	0.0021	0.0007	0.0708	0.4289
P46	0.0621	0.0003	0.0089	0.0008	0.0266	0.7984	0.0798	0.0053	0.0089	0.0089	0.1604
P47	0.0689	0.0002	0.1033	0.0003	0.0689	0.2870	0.4592	0.0006	0.0057	0.0057	0.5385

Table 4: Input and output data for (ANN, A.N.N-P.S. O) techniques (output=Delay)

Projects	Inputs										Outputs
	DF1	DF2	DF3	DF4	DF5	DF6	DF7	DF8	DF9	DF10	
P1	0.1109	0.0115	0.1109	0.0021	0.0053	0.0021	0.0021	0.0021	0.0021	0.0021	0.0208
P2											
P3											
P4											
P5											
P6	0.1027	0.0027	0.1324	0.0009	0.0009	0.0009	0.0027	0.0027	0.0027	0.0027	0.0426
P7											
P8											
P9											
P10	0.0584	0.0015	0.1327	0.0015	0.0436	0.0015	0.0003	0.0015	0.0015	0.0089	0.0426
P11											
P12											
P13	0.1151	0.0063	0.0716	0.0063	0.0135	0.0063	0.0063	0.0063	0.0063	0.0135	0.0426
P14	0.1487	0.0057	0.0589	0.0024	0.0190	0.0057	0.0007	0.0007	0.0040	0.0057	0.5213
P15	0.0584	0.0015	0.1327	0.0015	0.0436	0.0015	0.0003	0.0015	0.0015	0.0089	0.0208
P16	0.0435	0.0027	0.1546	0.0009	0.0435	0.0009	0.0009	0.0009	0.0009	0.0027	0.0208
P17	0.0553	0.0031	0.1678	0.0010	0.0191	0.0010	0.0010	0.0010	0.0010	0.0010	0.0208
P18											
P19											

To be continued

P20											
P21	0.1483	0.0097	0.0736	0.0026	0.0026	0.0026	0.0008	0.0008	0.0044	0.0061	0.0426
P22											
P23											
P24											
P25											
P26											
P27	0.1487	0.0057	0.0589	0.0024	0.0190	0.0057	0.0007	0.0007	0.0040	0.0057	0.0208
P28	0.0577	0.0049	0.1751	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0643
P29	0.1073	0.0093	0.1073	0.0025	0.0059	0.0059	0.0025	0.0025	0.0076	0.0008	0.0643
P30	0.0398	0.0154	0.0154	0.0072	0.0154	0.0970	0.0235	0.0113	0.0113	0.0154	1.0000
P31	0.0915	0.0034	0.0915	0.0034	0.0020	0.0020	0.0166	0.0078	0.0298	0.0034	0.2852
P32											
P33											
P34	0.0664	0.0039	0.1675	0.0002	0.0111	0.0002	0.0002	0.0002	0.0002	0.0014	0.0208
P35	0.1164	0.0049	0.1164	0.0020	0.0020	0.0020	0.0005	0.0005	0.0034	0.0034	0.1296
P36	0.0693	0.0041	0.1748	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0016	0.0426
P37											
P38											
P39											
P40											
P41	0.0273	0.0061	0.1261	0.0026	0.0484	0.0061	0.0008	0.0008	0.0273	0.0061	0.1731
P42											
P43	0.0682	0.0067	0.1718	0.0010	0.0010	0.0010	0.0010	0.0000	0.0000	0.0010	0.2387
P44											
P45											
P46	0.0964	0.0083	0.0686	0.0021	0.0547	0.0006	0.0037	0.0052	0.0068	0.0052	0.5213
P47	0.0854	0.0029	0.0509	0.0000	0.0682	0.0010	0.0029	0.0019	0.0278	0.0106	0.3210

4.3 Model architecture

The difficult and essential process in building the neural model is the definition of the network structure. The network must be continuously trained to find the network's optimum performance to obtain the minimal training and test errors and top (R) of validation data by doing the best characteristics of the ANN model, such as transfer functions, number of neurons, and max iteration.

Several trials and errors were made. The researcher believed that the optimal network for cost & delay model with minimal validation and highest correlation coefficient consists of five hidden nodes with 1000 max iteration and when Tansig activation function was used for hidden and outputs layer with 70% and 30% training and testing ratio respectively. Tables 5, 6, 7, and 8 show the different architecture of the ANN models to get the optimal structure of the model.

Table 5: Performance of the ANN model for different architectures (output = cost)

Number of Neurons	Train			Test		
	R	R ²	RMSE	R	R ²	RMSE
1	0.549	0.302	0.091	0.153	0.023	0.099
2	0.815	0.664	0.064	0.565	0.319	0.076
3	0.880	0.775	0.052	0.835	0.697	0.050
4	0.926	0.858	0.042	0.912	0.831	0.037
5	0.972	0.946	0.026	0.948	0.899	0.028

Table 6: Effect of Transfer Function on ANNs Performance (output=cost)

Activation Function		Train			Test		
Hidden	Output	R	R ²	RMSE	R	R ²	RMSE
Sigmoid	Sigmoid	0.692	0.479	0.095	0.276	0.076	0.097
Tansig	Tansig	0.972	0.946	0.026	0.948	0.899	0.028

Table 7: Performance of the ANN model for different architectures (output = delay)

Number of Neurons	Train			Test		
	R	R ²	RMSE	R	R ²	RMSE
1	0.935	0.875	0.084	0.902	0.814	0.095
2	0.987	0.975	0.036	0.973	0.946	0.035
3	0.991	0.983	0.030	0.984	0.969	0.026
4	0.983	0.966	0.042	0.932	0.869	0.052
5	0.995	0.991	0.022	0.986	0.971	0.024

Table 8: Effect of Transfer Function on ANNs Performance (Output=delay)

Activation Function		Train			Test		
Hidden	Output	R	R ²	RMSE	R	R ²	RMSE
Sigmoid	Sigmoid	0.798	0.637	0.409	0.713	0.508	0.420
Tansig	Tansig	0.995	0.991	0.022	0.986	0.971	0.024

It is demonstrated from the above Tables 5 to 8 that selecting of 5 neurons with Tansig activation function prompted better outcomes by having the highest value R and R², and the

least RMSE value. Hence, an ANN with a Tansig activation function, single hidden layer containing five neurons, was considered, as represented in Figure 2:

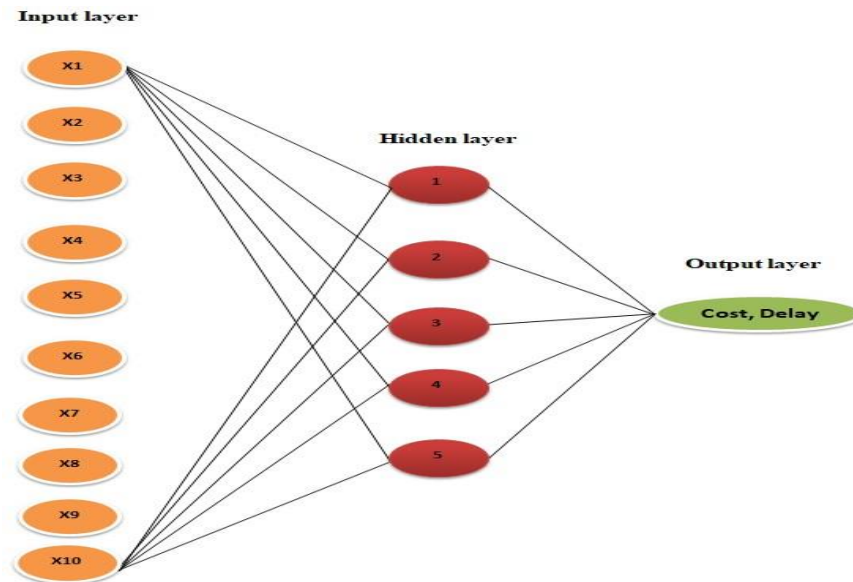
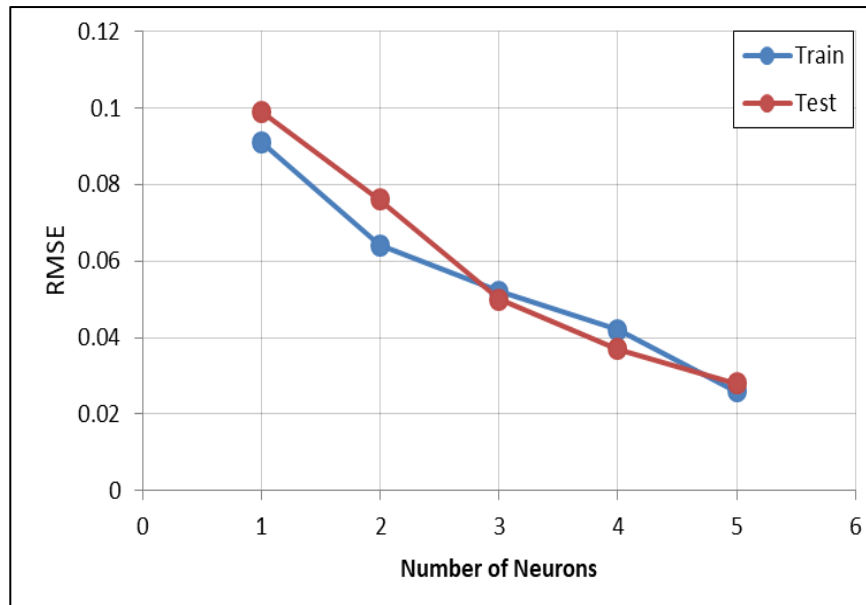


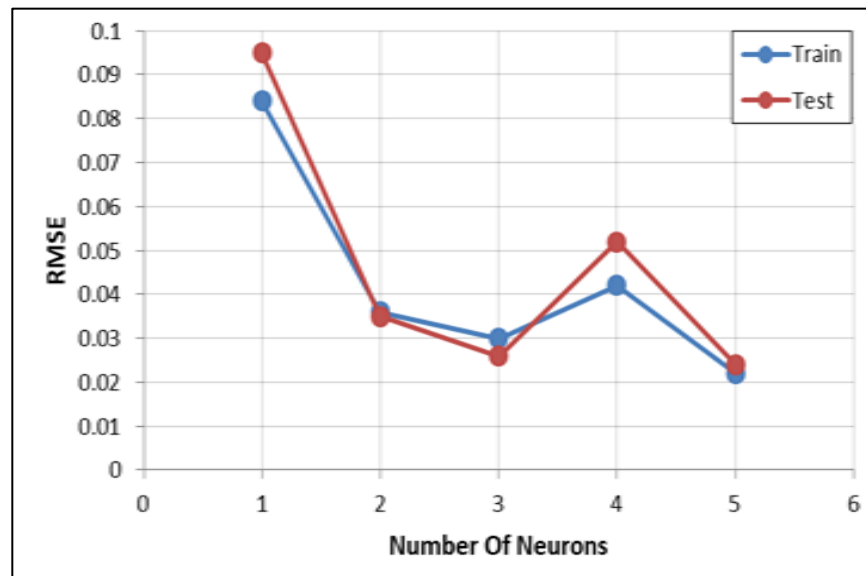
Figure 2. ANN architecture

The effect of the neuron's quantity on the RMSE is exhibited in Figure 3. The least RMSE

was recorded when the five neurons were chosen.



(a)



(b)

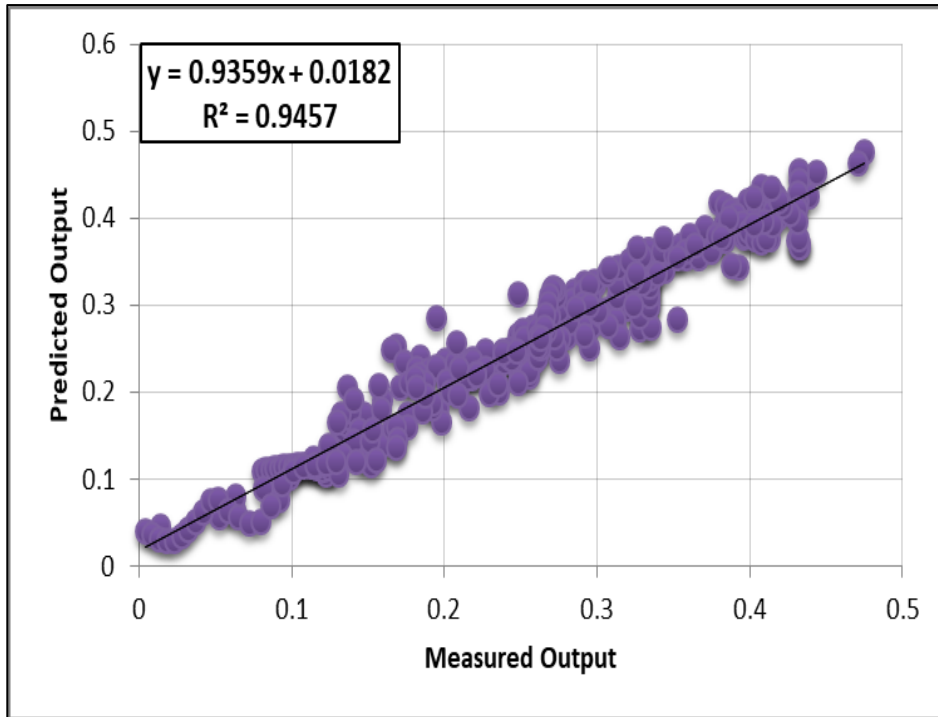
Figure 3. Impact of the number of neurons on RMSE value by using ANN-BP model: (a) Output = cost; (b) Output = delay

5. Results and discussion

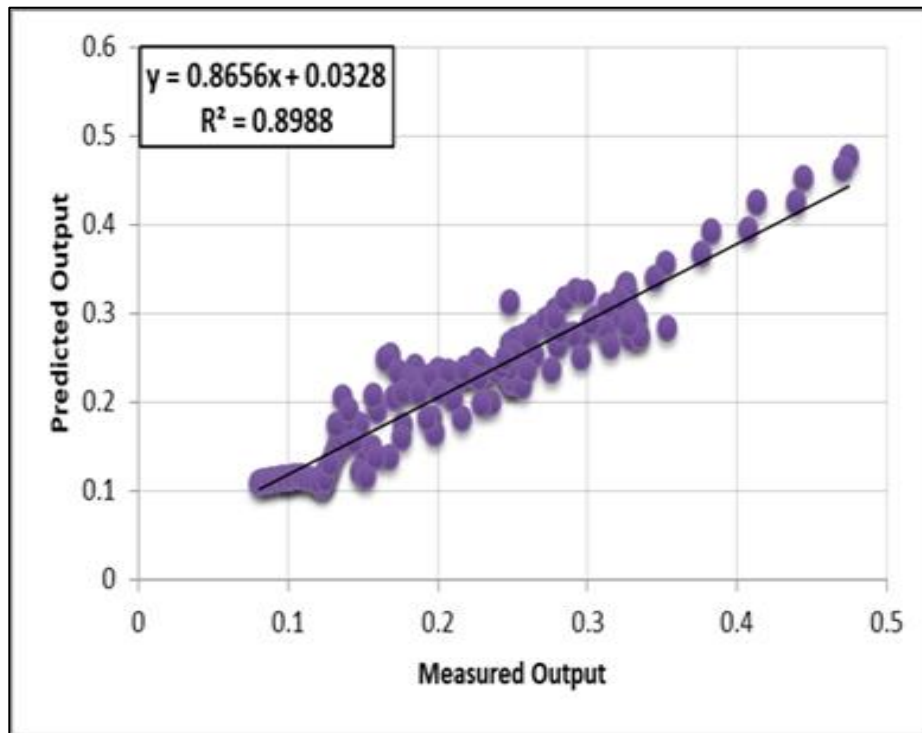
5.1 Development of models to predict cost and delay using ANN

ANN-BP model with the hyperbolic tangent activation function training by (BP) and (LMA) optimization algorithm was used as was mentioned above. It was observed that the optimal ANN model gave an acceptable performance was consisted of five neurons with a single hidden layer. Figure 4 showed the results of the training and testing phase of ANN-

BP model of cost prediction. The performance indices of ANN-BP model in the training phase were 0.972, 0.946, 0.026 for R, R², and RMSE consecutively, as indicated by Figure 4 (a). However, the performance indices of ANN-BP model in the testing phase were 0.948, 0.899, 0.028 for R, R², and RMSE, respectively, as demonstrated by Figure 4 (b). ANN-BP model showed superior performance in cost prediction since R and R² were closer to 1, and RMSE was lower than 1. Figure 5 shows the results of the ANN-BP model to predict the measured cost for each project in the testing phase.



(a)



(b)

Figure 4. (a): Training phase of the ANN-BP model, (b): Testing phase of the ANN-BP model

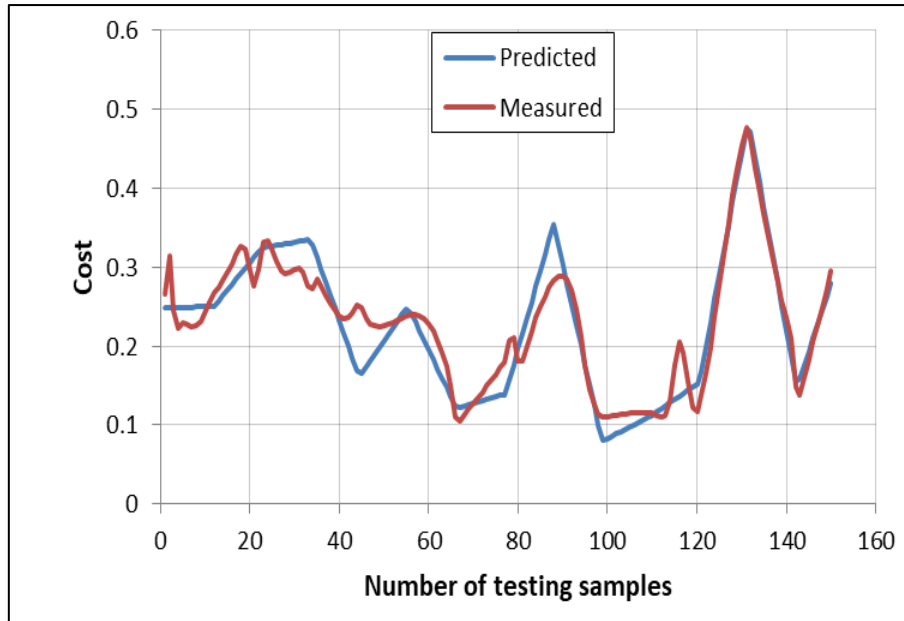
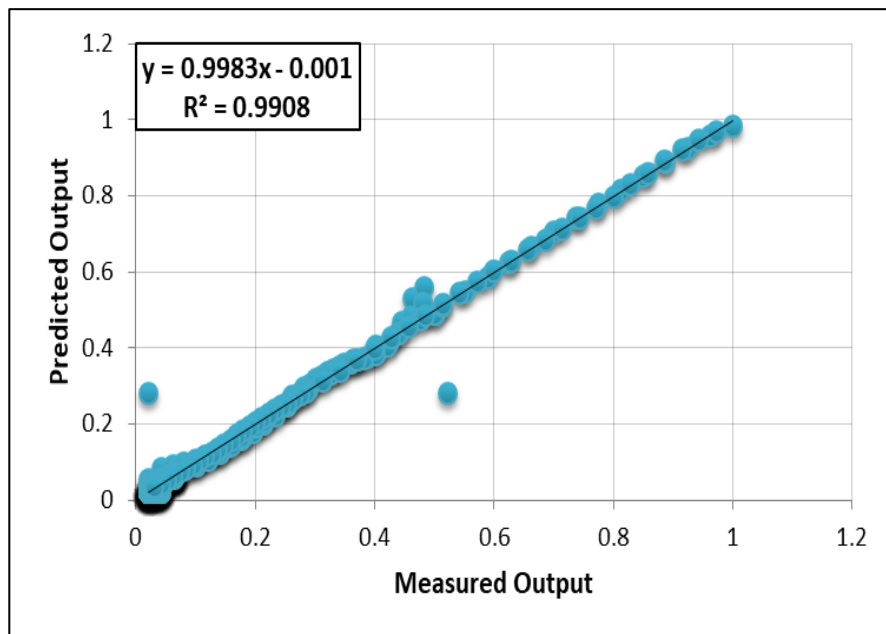


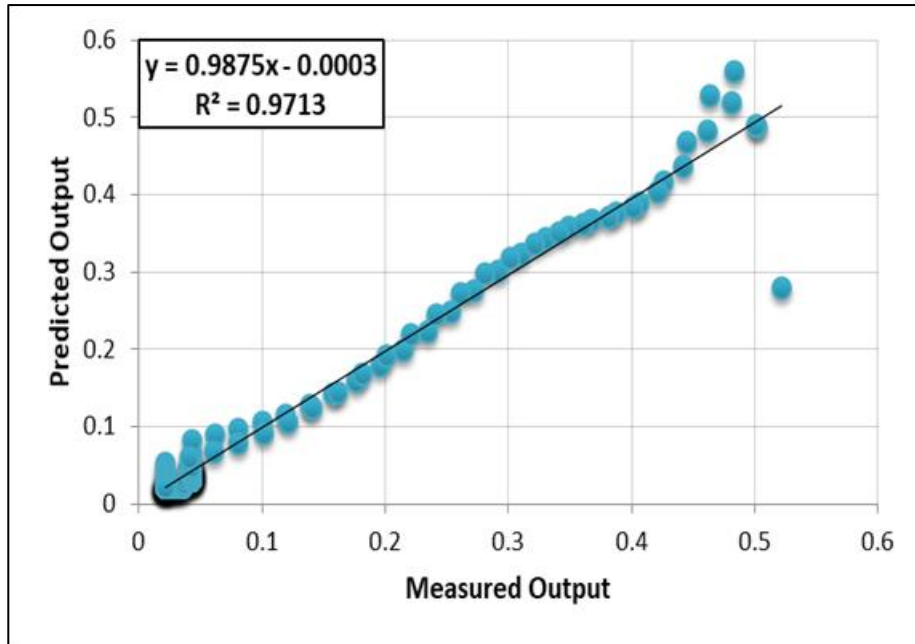
Figure 5. Cost prediction in the testing phase by using ANN-BP model

Figure 6 shows the results of ANN-BP model to predict delay. The performance indices of ANN-BP model in the training phase were 0.995, 0.991, and 0.022 for R, R², and RMSE, respectively, as demonstrated by Figure 6 (a). While, the performance indices of ANN-BP model testing phase were 0.986, 0.971, 0.024 for

R, R², RMSE, respectively, as shown in Figure 6 (b). ANN-BP model to predict delay showed better performance with higher values for R and R² and lower value of RMSE as compared with ANN-BP model to predict the cost. Figure 7 shows the results of the ANN-BP model to predict the measured delay for each project in the testing phase.



(a)



(b)

Figure 6. (a): Training phase of the ANN-BP model, (b): Testing phase of the ANN-BP model

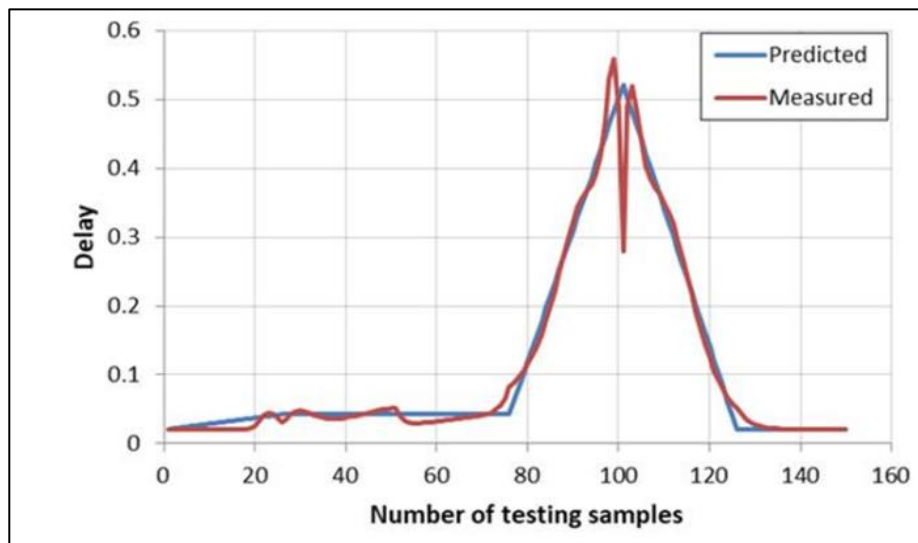
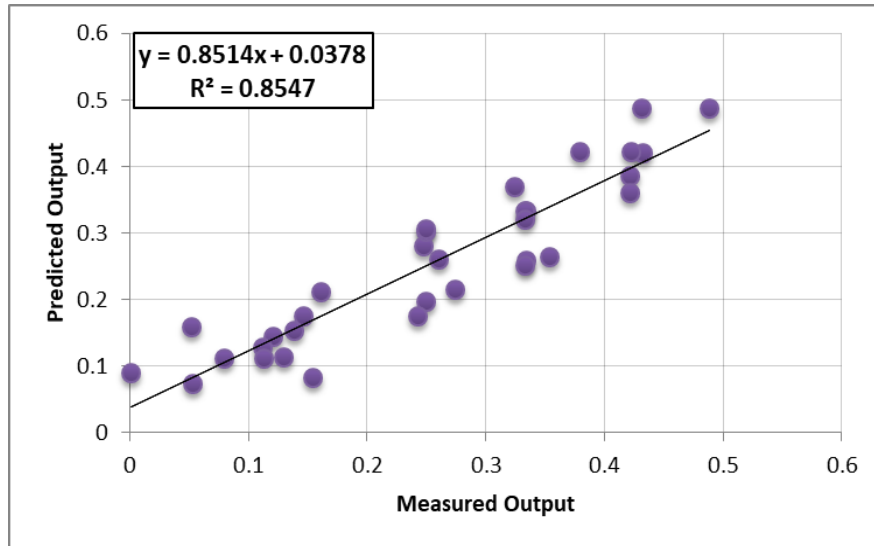


Figure 7. Delay prediction in the testing phase by using ANN-BP model

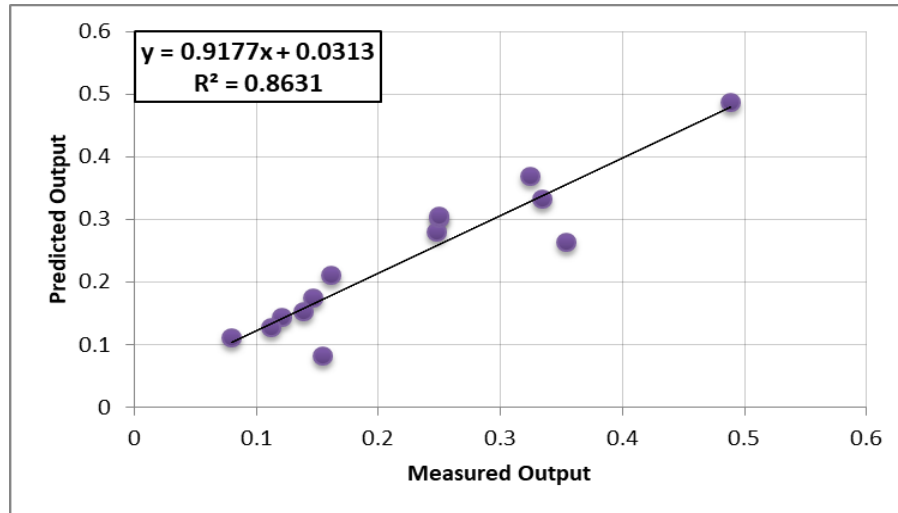
5.2 Development of models to predict cost and delay using ANN-PSO

The training and testing phase of ANN-PSO model showed acceptable results in predicting the cost as illustrated in Figure 8. The performance indices of ANN-PSO model in the training phase were 0.924, 0.855, 0.050 for R, R2, and RMSE, respectively. On the other hand, the performance indices' testing phase was

0.929, 0.863, and 0.044 for R, R2, and RMSE consecutively. The model exhibited a significantly high correlation since the values of R and R2 coefficients approached 1, and the RMSE value was practically low ranged from 0 to 0.05. Figures 8 (a) and (b) showed the training and testing phase of the ANN-PSO model. The predict and the measured cost for each project in the testing phase using the ANN-PSO model are illustrated in Figure 9.



(a)



(b)

Figure 8. (a): Training phase of the ANN-PSO model, (b): Testing phase of the ANN-PSO model

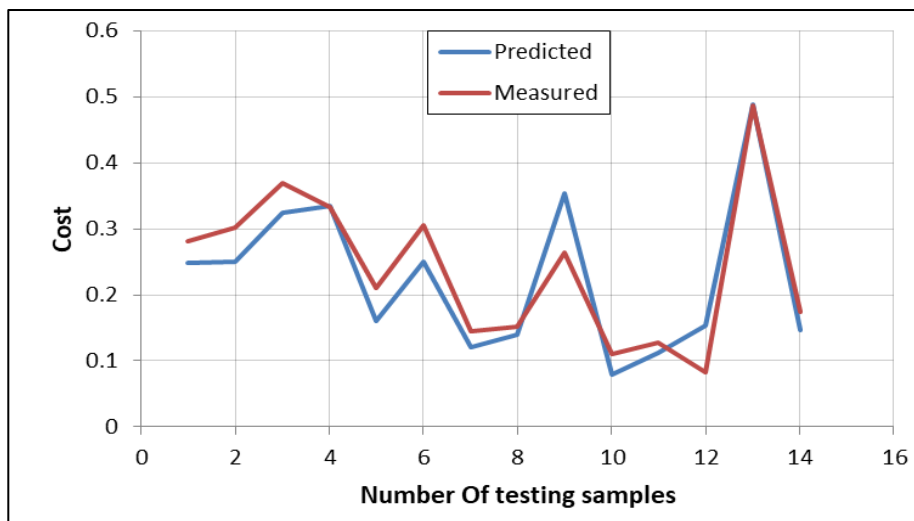
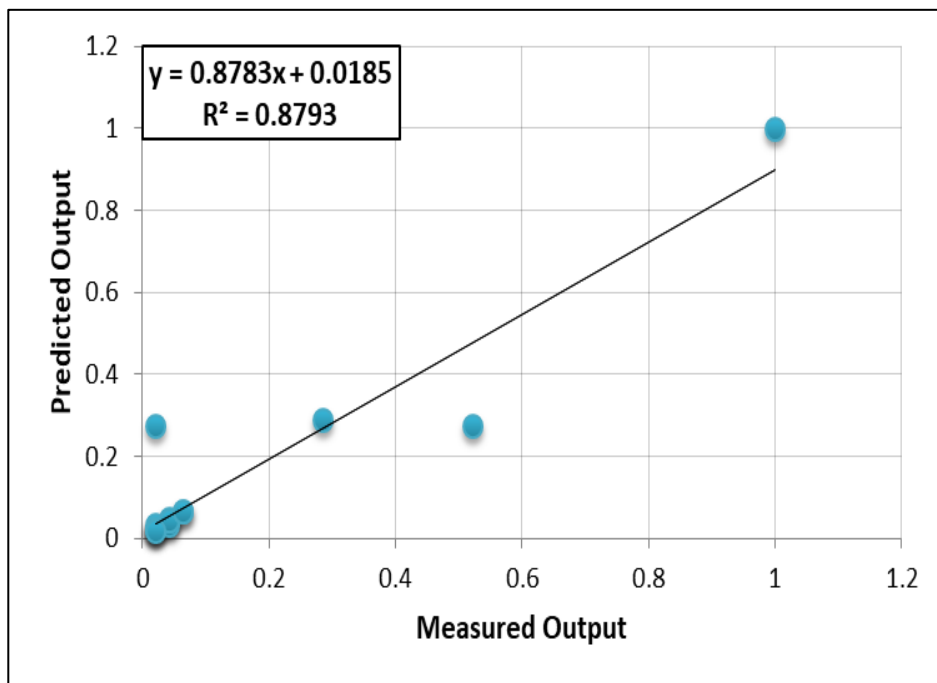


Figure 9. Cost prediction in the testing phase using ANN-PSO model

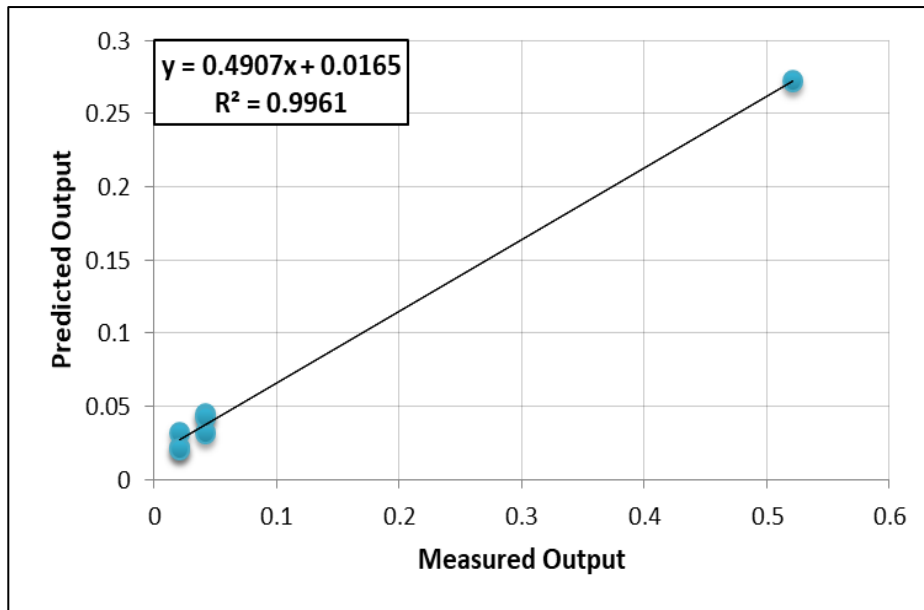
Figure 10 shows the results of the ANN-BP model to predict the delay in scatter diagrams to demonstrate the relation between the measured and actual delay. The performance indices of ANN-PSO model in the training phase were 0.938, 0.879, and 0.091 for R, R², and RMSE, respectively, as shown in Figure 10 (a). while the performance indices in the testing phase were 0.998, 0.996, and 0.094 for R, R², and RMSE demonstrated in Figure 10 (b). It is demonstrated that ANN-PSO model in the delay prediction was better than the cost prediction based on the values of R and R², and RMSE. Figure 11 shows results of the ANN-PSO model to predict the measured delay for each project in the testing phase.

To sum up, ANN-PSO model showed significant results. However, the ANN-BP model was better than ANN-PSO in the

prediction of cost and delay. Similar observations were recalled by Tareq et al.2020 [15]. He proposed PSO to the estimation of construction costs and duration of construction projects. A series of 60 projects collected from constructed government projects were utilized to build the proposed models. Eight input parameters, such as volume of bricks, the volume of concrete, footing type, elevators number, total floors area, ground floor area, floors number, and security status, are used to build the proposed model. The results displayed that the PSO models can be an alternative approach to evaluating construction projects' cost and /or duration. The developed model provided high prediction accuracy 0.97 and 0.99, with a low mean. A comparison of the models' results indicated that predicting with PSO was importantly more precise.



(a)



(b)

Figure 10. (a) Training phase of the ANN-PSO model, (b) Testing phase of the ANN-PSO model

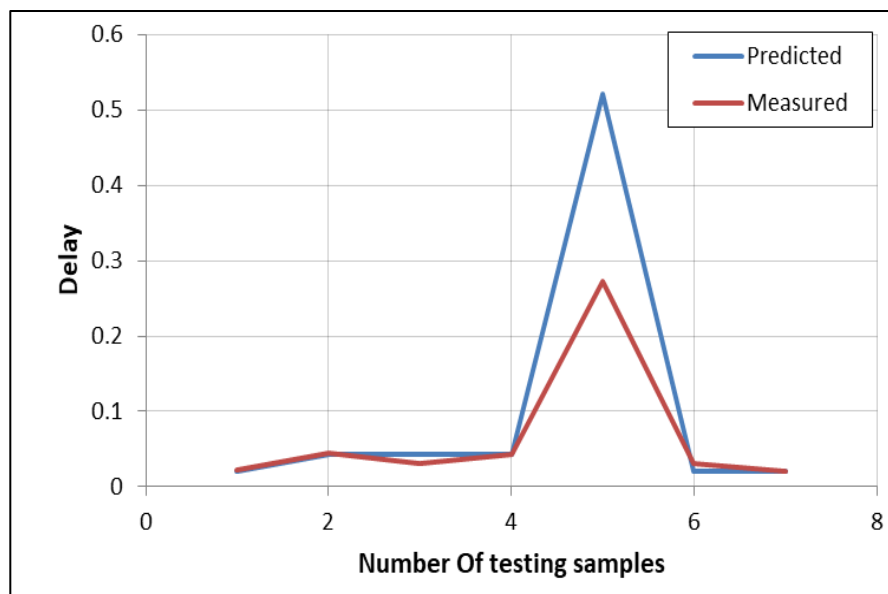


Figure 11. Delay prediction in the testing phase using ANN-PSO model

6. Conclusions

Based on the investigations done in this study, the following conclusion are drawn:

- The current study examined the capability of ANN-BP and ANN-PSO models in the cost–delay prediction of 47 construction projects.
- The developed ANN-BP model with the Levenberg–Marquardt algorithm (L.M.A.) had good accuracy in predicting cost and delay of construction projects. ANN-BP model in the delay prediction was better than in cost prediction for the construction projects.
- The ANN-PSO model with ten particles and five neurons showed significant cost and delay prediction performance.
- Both models ANN-BP and ANN-PSO, showed acceptable results in cost and delay prediction. However, the optimal model

based on performance indices (R , R^2 , RMSE) in the cost prediction was the ANN-BP model. In contrast, the ANN-PSO model was the optimal model in delay prediction based on performance indices (R , R^2) and RMSE.

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