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Artificial Neural Network Model for Wastewater Projects Maintenance Management Plan

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ABSTRACT

Wastewater projects are one of the most important infrastructure projects, which require developing strategic plans to manage these projects. Most of the wastewater projects in Iraq don't have a maintenance plan. This research aims to prepare the maintenance management plan (MMP) for wastewater projects. The objective of the research is to predict the cost and time of maintenance projects by building a model using ANN. The research sample included (15) completed projects in Wasit Governorate, where the researcher was able to obtain the data of these projects through the historical information of the Wasit Sewage Directorate. In this research artificial neural networks (ANN) technique was used to build two models (cost and time) for the maintenance of wastewater projects. The output shows there is a high correlation (R) between real and expected cost with 95.4%, minimized testing error (8.5%), and training error (19%). The mean absolute present error (MAPE) and Average Accuracy Percentage (AA) are (13.9% and 86.1%) respectively. Also, the results showed a strong correlation (R) between actual and predicted time (99.1%), minimized testing error (8%), and an additional MAPE% and AA% with (11.7% and 88.3%) respectively. These models are in agreement with the real values, as well as gives good prediction for future maintenance projects.

Keywords: Artificial neural networks, cost model, time model, Maintenance Management Plan, wastewater projects

نموذج الشبكة العصبية الاصطناعية لخطة ادارة صيانة مشاريع الصرف الصحي

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الخلاصة

تعتبر مشاريع الصرف الصحي من أهم مشاريع البنية التحتية والتي تتطلب وضع خطط إستراتيجية لإدارة هذه المشاريع. معظم مشاريع الصرف الصحي في العراق ليس لديها خطة صيانة.ان الهدف الرئيسي من هذا البحث هو إعداد خطة إدارة الوقت والتكلفة لمشاريع الصيانة. اشتملت عينة البحث على (15) مشروعاً منجزاً في محافظة واسط حيث تمكن الباحث من الحصول على بيانات لهذه المشاريع من خلال المعلومات التاريخية لمديرية مجاري واسط. تم استخدام تقنية الشبكات العصبية الاصطناعية (ANN) للتنبؤ بوقت وتكلفة مشاريع مياه الصرف الصحي من خلال بناء نموذجي التكلفة والوقت. أظهرت النتائج الى وجود علاقة ارتباط قوية بين التكلفة الفعلية والتكلفة المتوقعة بنسبة 95.4٪ وأدنى خطأ في الاختبار (8.5٪) وخطأ التدريب (19٪). تم العثور على نسبة MAPE ومتوسط الدقة الناتجة عن نموذج ANN لتكون (13.9٪) و (86.1٪) على التوالي. كما أظهرت النتائج وجود علاقة ارتباط قوية بين الوقت الفعلي والمتوقع بنسبة (99.1٪) ، وأدنى خطأ في الاختبار (8٪). تم العثور على نسبة MAPE ومتوسط الدقة الناتجة عن نموذج ANN لتكون (11.7٪) و (88.3٪) على التوالي. هذه النماذج تظهر توافقاً جيداً مع القياسات الفعلية. كما أن هذا النموذج يعطي تنبؤًا جيدًا لمشاريع الصيانة المستقبلية.

الكلمات الرئيسية: الشبكة العصبية الاصطناعية, نموذج التكلفة, نموذج الزمن, خطة ادارة الصيانة, مشاريع الصرف الصحي

1. INTRODUCTION

The maintenance management plan (MMP) defines the record compilation in the form of computer files that describe the scheduling, planning, documentation, and reporting of preventative maintenance activities and provides a method of recording unscheduled or corrective maintenance activities. Wastewater projects have an important role in construction projects. This reason leads to develop MMP **(Eren and Gencer, 2016)**. The research strategy is to prepare a future maintenance management plan (MMP)for wastewater projects as a five-year plan. The research method was conducted by data collection (historical data) from Wasit Sewage Directorate, which includes (15) completed projects; the historical data is considered as input that enters the NEUFRAM V.4 program. The research adopted an artificial neural network (ANN) approach to build cost and time model to predict the cost and time maintenance project of wastewater. A lack that occurs in one of the MMP increases the project's problem **(Düzakın and Demircioğlu, 2005)**. The effective use of MMP leads to successful wastewater projects. The lack of the most appropriate MMP creates uncertainty in diagnosing the defects. MMP plays the main role in conducting the safe and sustainable performance of the wastewater project. The development in technology makes it able to apply to many areas of wastewater projects in maintenance activities **(Ahmad and Kamaruddin, 201)** .

The essential to the success of MMP is the evaluation of all aspects of the project, such as time, cost, and quality. Artificial neural networks have two main benefits: storage capacity and classification speed, in addition to the ability to store many complex patterns such as visual scenes, speech templates, and robot movements **(Zidan, 2008).** ANN is an artificial intelligence application that mimics the human brain in solving problem processes. As a new problem is solved based on past experience, a neural network takes previously solved cases, looks for patterns in these examples, applies the pattern, and develops the ability to correctly classify new patterns and predict and forecast process parameters **(Zhang, 2002)**.

Artificial neural networks (ANN) can be used in several aspects because of technological improvement. Compared with other estimation methods, ANN gives the best results in cost and time prediction **(Ali et al., 2015)**. In this research, the ANN model provides the future prediction using the effecting factors as input. The implemented MMP caused a minimization in the defects and downtime of projects in this study, including general information on neuframe program V.4, the effect of data division on the model, architecture of the neural network of the model, the effect of momentum term on the model, effect of learning rate model, the effect of transfer function on model. The aim of this research is to prepare the maintenance management plan (MMP) for wastewater projects using the ANN technique by building a cost and time model.

2. LITERATURE REVIEW

The study of **(AL-Saadi et al., 2017)** aimed to estimate the time of highway projects in the republic sector of Iraq. The data collection was conducted using historical data for the interval between 2000 to 2017. The total number of projects is 99 from the Roads and Bridges Directorate (RBD). The researcher used the ANN technique to predict the duration. The methodology in this study involved two main parts; the first part contains the literature review of the subject, and the second part, is the practical part that used the Neuframe V.4 program to build the models to predict the duration of road projects. The output shows a high correlation between real duration and expected duration (90.6%), less testing error (3.2%), and training error (4.9%). The mean absolute present error MAPE and Average Accuracy Percentage (AA) are (25.73 %) and (74.27%) respectively. Therefore, it can be concluded that the ANNs model show very good agreement with the actual measurements. In the study by **(El Fahham, 2019),** predicting construction costs and estimating price escalation were the main steps for project owners, estimators, and contractors. The construction cost index (CCI) is widely used to predict project costs. This study uses the equation for calculating the CCI for construction projects. The researcher concluded that this study provides construction stakeholders with a reliable tool for predicting the cost of coming projects, especially under the existing inflation condition. While **(Pessoa et al., 2021)** discussed the implementation of construction projects often includes the financial resources not foreseen during the bidding, which causes problems in management. The purpose of this study is a build the model using ANN in order to estimate the cost of construction projects in Brazilian. The results showed the mean absolute percentage errors (MAPE), and coefficient of correlation (R) are (5% and 99%) respectively. **(Al-Zubaidy et al., 2022)** conducted to expect shear strength factors of gypseous soils according to soil properties was prepared using ANN. The researcher built two models to predict the cohesion and the angle of internal friction. The input included nine main soil properties in both models. The structure of ANN was multi-layer perceptron training, and back propagation algorithm was used in training the network. The researcher concluded that both models could forecast shear strength parameters for gypseous soils with good reliability. At the same time, the result of the second model indicated that the gypsum include and plasticity index have the most significant effect on the expected angle of internal friction. This research differs from other similar studies as follows: prepare MMP using ANN technique in wastewater projects, two models were built (cost and time model), and the case study was conducted in Wasit governorate for wastewater projects (nets and pump stations).

3. PROGRAM OF NEUFRAME V.4

Nuframe V.4 is an integrated set of artificial intelligence techniques that use the logic of neural networks, and it requires a reasonable level of computer system resources **(Sahar,2011)**. **Fig. (1)** shows the general ANN diagram of Neuframe4 to determine the relationship between explanatory variables as input and response variables as output. ANN includes many units called nodes, connection weights that link each node to the other nodes. These weights describe the information used by the net to solve the case to be solved. The network structure is composed of many layers, and the input layer (dependent variables) is applied to the net. The outputs layer (independent) is extracted. A number of nodes serve as preceding items in the hidden layers between the input and output **(Al-Musawi, 2016)**. The ANN technique can represent linear and nonlinear relationships from modeled data **(Lal and Tripathy, 2012)**.

The input element in the previous layer (xi) is multiplied by connection weight (wij) at each processing element, the weighted input signals are summed, and bias value (θj) may be added. This combined input (Ij) is then passed through a transfer function f(Ij) to produce the output of the processing element (yj). This process is illustrated in equations (1) and (2) **(Al-Janabi, 2006)**.

$$Ij = \Sigma wjixi + \theta j \quad (1)$$

$$yj = f(Ij) \quad (2)$$

where:
Ij: Activation level of node (j),
wji: weight of the connection between (j) and (i),
xi: Input from node (i) for (i = 0, 1… n),
θj: Bias or threshold for node (j),
yj: Output of node (j), and
f(Ij): Transfer (activation) function.

The artificial neural network (ANN) technique has been used for the following reasons: its ability to predict, by providing it with real inputs, the ability to learn and get the least testing error by training because it has a feature of back propagation, able to obtain the high coefficient of correlation and least testing error by building the network architecture (choosing the optimal number of hidden layers) by trial and error.

4. COST AND TIME MODEL

The steps of building cost and time model include determining the effecting factors (variables) as input on maintenance time which is (X_1: the sector, X_2: type of maintenance, X_3: element of maintenance, X_4: type of contract, X_5: experience of project manager, X_6: No. of the change order and X_7: market condition). (F_1: site condition, F_2: safety and security, F_3: type of contract, F_4: type of maintenance, and F_5: degree of risk), as shown in **Tables 1**. and **2**. The data collections based on historical data from Wasit Sewage Directorate include networks and pump stations.

Table 1. The input of ANN in the cost model

Project	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Actual cost/ID
M_1	1	1	30	1	15	3	1	15000000
M_2	2	1	40	3	20	1	1	11000000
M_3	1	1	20	1	25	2	3	13300000
M_4	2	1	25	1	30	1	2	9400000
M_5	1	2	22	2	15	1	3	9300000
M_6	1	1	21	3	22	2	2	13000000
M_7	2	1	15	3	15	1	2	10500000
M_8	1	1	18	2	20	2	2	14670000
M_9	1	1	12	2	18	1	3	12000000
M_{10}	2	2	11	1	30	1	3	10500000
M_{11}	1	1	14	2	16	1	1	13000000
M_{12}	1	1	10	1	12	1	2	15000000
M_{13}	1	2	5	1	18	1	2	10680000
M_{14}	2	2	15	1	18	2	2	12587000
M_{15}	1	2	12	2	18	2	1	11880000
Min	2	2	40	3	30	3	3	9300000
Max	1	1	5	1	12	1	1	15000000
Range	1	1	35	2	18	2	2	5700000

Table 2. The input of ANN in the time model

Project ID	F1	F2	F3	F4	F5	Actual time/day
M_1	1	1	1	1	3	16
M_2	1	2	3	1	2	15
M_3	1	1	1	1	2	15
M_4	2	2	1	1	2	20
M_5	1	1	2	2	2	18
M_6	2	1	3	1	2	15
M_7	1	2	3	1	3	20
M_8	1	1	2	1	3	20
M_9	1	1	2	1	1	15
M_{10}	2	2	1	2	1	20
M_{11}	2	1	2	1	3	15
M_{12}	1	1	1	1	1	18
M_{13}	1	1	1	2	2	15
M_{14}	2	2	1	2	2	15
M_{15}	1	1	2	2	2	15
Max	2	2	3	2	3	20
Min	1	1	1	1	1	15
Range	1	1	2	1	2	5

4.1 Data Division

The data division is necessary for a successful neural network and to determine the information presented to build the model in the training phase. The next step in ANN models is to divide the data into three subsets: training, testing, and validation. In the training set, the learning prosses is performed, which is used for estimating the weights. The testing set is used for measuring the generalization ability of the network and assessing the network performance. The results clarify that the minimum testing error with (8.5%) and (R) was (95.4%) as well as the best division of data for the cost model is equal to (70%) for the training set, while (15%) for validation set and (15%) for the testing set. The different choice for divisions (random, blocked, and striped) was investigated. The best performance was obtained when the blocked division was used, as shown in **Table 3**.

Data were divided based on the highest coefficient of correlation (R) by (99.1%) and the lowest testing error (8%), where the data division for the training set is (75%), and the test set (10%) as shown in **Table 4.**

Table 3. Effect the data division on the ANN model

Data division %			Choices of division	Testing error%	R %
Training	Testing	Validation			
70	15	15	Stripe	13.4	18
70	15	15	Block	8.5	95.4
70	15	15	Random	14.9	93.3

Table 4. Effect the data division on the ANN model

Data division %			Choices of division	Testing error%	R%
Training	**Testing**	**validation**			
75	10	15	Striped	14	66.6
75	10	15	Blocked	8	99.1
75	10	15	Random	10.5	50.1

4.2 Scaling of Data

The data is divided into three subsets. The input and output variables are preprocessed by scaling them to remove their dimensions and guarantee that each variable receives equal attention during training. The measurement should be proportional to the range of the transmission function used in the hidden and output layer (-1.0 to 1.0) for the tanh transfer function and 0.0 to 1.0 for the sigmoid transfer function). The scaled value (Xn) is found by equation (3) **(Mahmood and Aziz, 2011)**.

$$Xn = \frac{X - Xmin}{Xmax - Xmin} \quad (3)$$

Where:
Xn: Scale value
X: Original value
X_{min} and X_{max}: Minimum and maximum original value

4.3 Momentum Term

The internal parameters affect the back-propagation algorithm (learning rate and momentum term) on the model's performance. **Table 5** shows the effect of the momentum term, and it can be seen that the obtained best value for the momentum term is 0.8, which has the highest coefficient of correlation (R) of (95.4%), and the minimum testing error is (8.5%). **Table 6 s**hows the momentum term is (0.8), which has the highest coefficient of correlation (R) of (99.1%), and the minimum testing error is (8.5%)

Table 5. Effect of momentum term on the cost model

Parameter effective	Testing error%	Training error%	Momentum term	R%
Model No. 1 Choices of division (blocked) No. of nodes (1) Transfer function in the hidden layer (Sigmoid) Transfer function in the output layer (Sigmoid)	8	18.5	0.01	93.4
	8.5	18.3	0.05	93.5
	9	19.5	0.1	93.5
	8.6	18	0.2	93.6
	8.3	18	0.3	93.6
	8	18	0.4	93.7
	8	18	0.5	93.8
	9	18.5	0.6	94
	8.37	19	0.7	94.4
	8.5	17	0.8	95.4
	10	19.6	0.9	76.6
	7	4.9	0.95	47

Table 6. Effect of momentum term on the time model

Parameters Effect	Testing error%	Training error%	Momentum Term	R%
Model No. 1 Choices of division (blocked) Learning Rate (0.2) Number of Nodes (1) Transfer (activation) function in the hidden layer (Sigmoid) Transfer function in the output layer (Sigmoid)	8.5	14	0.02	97
	8.9	15	0.06	97.5
	7.6	15.5	0.2	98.2
	8.5	14.5	0.3	98.7
	8.4	14.8	0.4	98.6
	7.8	14.2	0.5	98
	8	14	0.5	98.5
	7.4	14.4	0.4	96.9
	7.3	13	0.7	99.2
	8	10.5	0.8	99.1
	8.8	16	0.9	99

4.4 Rate of learning

This model plays an important role in enhancing the neural network performance, as the learning rate identifies the speed of change of slope and bias, and the effect of the learning rate was achieved when the best value of the momentum term is (0.8), as shown in **Table 7**. The researcher noted that the optimal value of the learning rate is (0.2) and minimum testing error (8.5%), training error (19%), and the maximum coefficient of correlation (R) is (95.4%). **Table 8** shows the optimal value of the learning rate (0.2), which has less testing error (8%) and the maximum coefficient of correlation (99.1%), and then it is used in the time model.

Table 7. Effect of learning rate on the cost model

Parameters Effect	Testing error%	Training error%	Learning rate	R%
Model No. 1	8	18.5	0.05	93.5

Choices of division (blocked) Momentum term (0.8) No. of nodes (1) Transfer function in the hidden layer (Sigmoid) Transfer function in the output layer (Sigmoid)	8.5	18.7	0.1	94
	8.5	19	0.2	95.4
	9	19.5	0.3	92.5
	8.4	17	0.4	77.7
	8	18	0.5	71.8
	8.5	15	0.6	51
	8.2	12	0.7	48
	7.6	6	0.8	56.6
	7	6	0.9	53.7
	7.9	5	0.95	48.8

Table 8. Effect of learning rate on the cost model

Parameters Effect	Testing error%	Training error%	Learning rate	R%
Model No. 1 Choices of division (striped) Momentum Term (0.8) No. of Nodes (1) Transfer function in the hidden layer (Sigmoid) Transfer function in the output layer (Sigmoid)	7.4	14	0.04	99
	7.9	14.9	0.1	98.5
	8	12	0.2	99.1
	10	12.5	0.3	99
	9.5	12.6	0.4	97.9
	8.8	13	0.5	97.7
	9.4	10	0.6	95.5
	10.3	9.5	0.7	96.6
	8.7	9.7	0.8	96.4
	11	8.5	0.9	97.5
	10.2	9.8	0.95	98.3

4.5 Transfer Function

Four tests check the transfer function in each neural network model. The researcher concluded that the neural network performance is not affected by function type, and the best ANN performance was the sigmoid function as the coefficient of correlation was (95.4%), and the minimum testing error was (8.5%) for both output and hidden layers, as shown in **Table 9**. The effect of transformation functions in the time model such as (tanh and sigmoid) was studied as illustrated in **Table 10.** The best performance was obtained when using the sigmoid transfer function for each of the hidden and output layers in a model.

Table 9. Effect of transfer function on the cost model

Parameters Effect	Transfer function		Training error%	Testing error%	R%
	Hidden Layer	Output Layer			
Model 1 Choices of division (blocked) No. of nodes (1) Momentum term (0.8) Learning rate (0.2)	Sigmoid	Sigmoid	19	8.5	95.4
	Sigmoid	tanh	9	6	32.5
	tanh	Sigmoid	19	8.5	77
	tanh	tanh	6.6	5.5	10

Table 10. Effect of transfer function on the cost model

Parameters effect	Transfer Function		Testing Error %	(R) %
	Hidden Layer	Output Layer		
Learning rate (0.2) Momentum term (0.8) No. of nodes (1)	Sigmoid	Sigmoid	8	99.1
	Sigmoid	Tanh	9.5	90.4
	Tanh	Sigmoid	7.5	95.5
	Tanh	Tanh	16.7	94.4

4.6 Final Equation of Cost and Time Model

The researcher was able to obtain the least number of contact weights through the NeuframeV.4 program for the best structure of the model ANN, as shown in **Fig 1. and 2,** which allows translating the network into a simple formula, while the connection weights and (bais) as shown in **Table 11**, and **Table 12**.

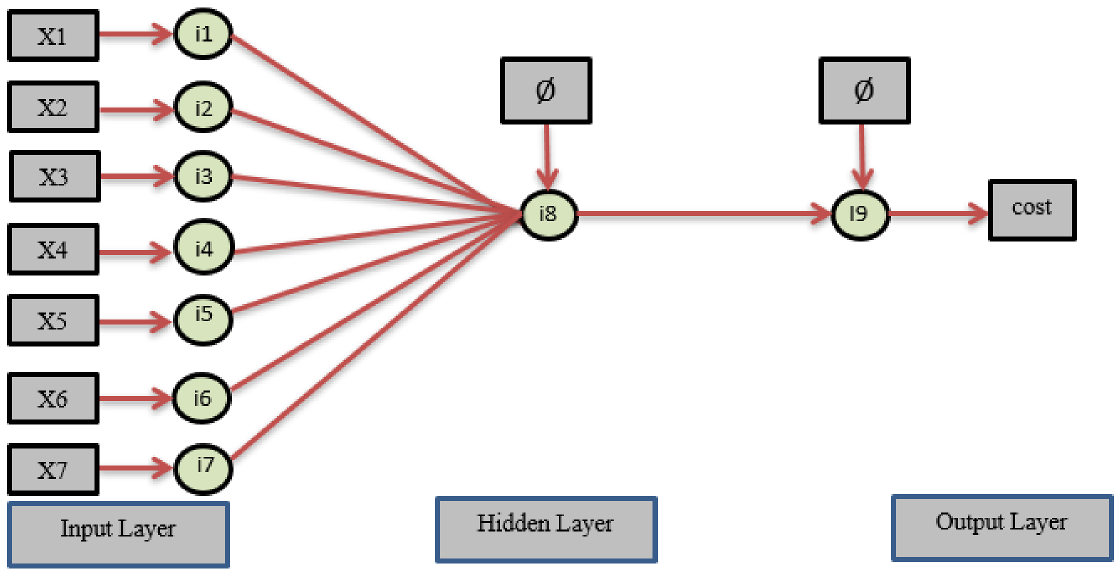

Figure 1. Structure of cost model

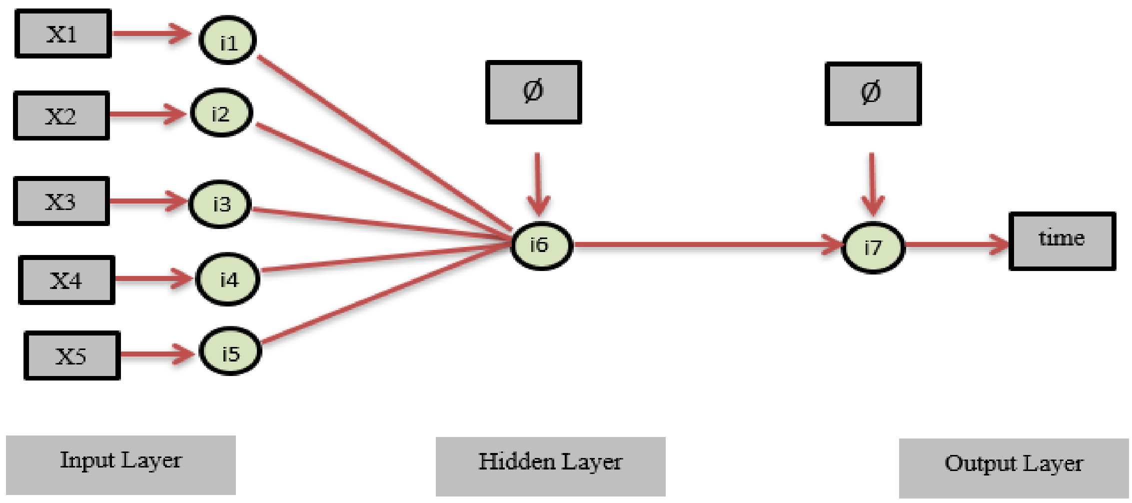

Figure 2. Structure of time model

Table 11. Weights and threshold levels of cost model

Hidden layer nodes	Wji (weight from node i in the input layer to node j in the hidden layer)							Hidden layer threshold θ
	i=1	i=2	i=3	i=4	i=5	i=6	i=7	
J=8	0.4261	0.1676	-0.3858	0.0404	-0.0383	-0.3131	-0.5123	0.4151
Output layer node	i=8							Output layer threshold θj
J=9	0.4229							-0.6620

The predicted cost can be formalized when using connection weight and bias; also, all input variables are converted to the scaled value, between 0.0 and 1.0, as shown in equation (4).

$$\text{Predicted cost} = \frac{5700000}{1+e^{-(0.422952*tanhX-0.66205)}} + 9300000 \quad (4)$$

Where :
X = 0.426142X1 + 0.167666X2 -0.05513X3 + 0. 0.020205X4 - 0.00639X5 -0.15656X6 - 0.25615X7 + 0.415126
For example, the case No. 13 in Table (1),
X1 = (1), X2 = (2), X3 = (5), X4 = (1), X5 = (18), X6 = (1), X7 = (2). When applying equation (4), the predicted cost is (10656447), compared with the actual cost is (10680000), which indicates the model gives agreement with the actual result.

Table 12. Weights and threshold levels of the time model

Hidden layer nodes	Wji (weight from node i in the input layer to node j in the hidden layer)					Hidden layer threshold θ
	i=5	i=4	i=3	i=2	i=1	
J=6	-0.5398	-0.9471	0.9269	-0.0249	2.0216	-0.7974
Output layer nodes						Output layer threshold θj
	i=6					
i=7	5.6106					-3.4106

$$\text{Predicted time} = \frac{5}{1+e^{-(5.6106*tanhX-3.4106)}} + 15 \quad (5)$$

Where:
X = 2.02166F1 - 0.0249F2 + 0.4634F3 - 0.94718F4- 0.2699F5 + 0.79747

For example, case No. 15 in **Table 2** X1 = (1), X2 = (2), X3 = (2), X4 = (2), X5= (2)
When applying equation (5), the predicted time is (15), compared with the actual time is (15.002), which indicates the model gives agreement with the actual result.

4.7 Validation of Cost and Time Model

According to **(Khaled et al., 2014)** and **(Almusawi and Burhan, 2020),** the statistical measures shown in **Tables 13** and **Table 14** are used to achieve the model and ensure its applicability in practice .

1. Mean absolute percentage error, MAPE=(∑(│A-E│)/A*100%)/n.
2. Average accuracy percentage, AA% = 100% - MAPE.
3. Coefficient of correlation (R).
4. Coefficient of determination (R2).

Table 3. Validity of cost model

Description	Statistical parameters%
MAPE	13.9
AA	86.1
R	95.4
R^2	91.01

Table 14. Validity of time model

Description	Statistical parameter%
MAPE	11.7
AA	88.3
R	99.1
R^2	98.2

Fig. 3. and **Fig. 4** show the evaluation of the validity of the cost and time model for ANN. The coefficient of correlation (R) is (95.4%) and (99.1%), respectively.

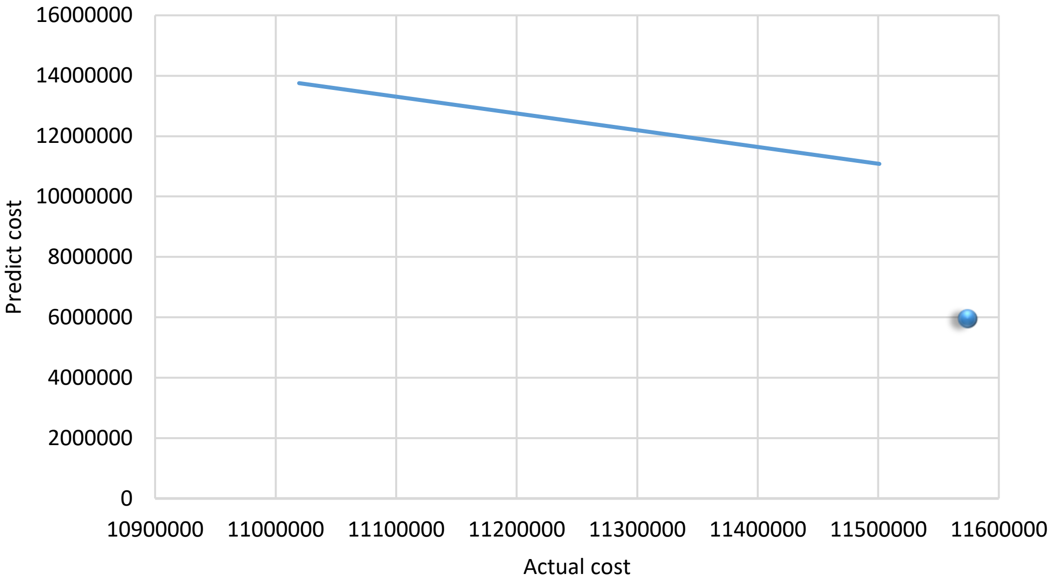

Figure 3. Comparison between actual and predicted cost

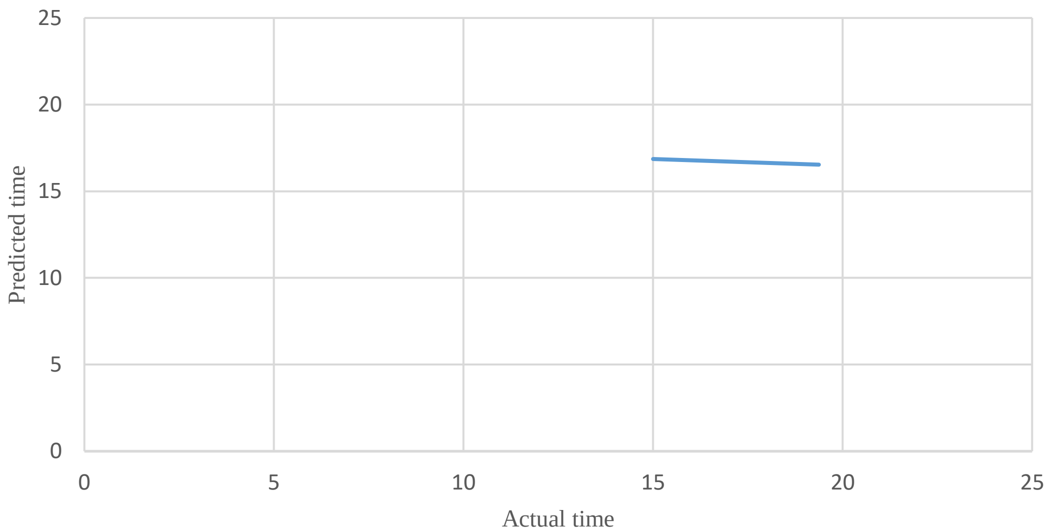

Figure 4. Comparison between actual and predicted time

5. CONCLUSIONS

According to the results obtained from the artificial intelligence technology, it has been concluded that the models (cost and time) built from artificial neural networks (ANN) gave agreement with actual values for the costs and time of maintenance of wastewater projects with a high coefficient of correlation of (95.4% and (99.1%), respectively. The least percent error (MAPE) was (13.9%) and (11.7%), respectively. In addition, these models help the decision makers predict maintenance projects' costs and time.

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Appendix A

Table A.1. Detail research sample

Project code	Project name	Cost/ID	Time/Day
M1	Rehabilitation of Tammuz Sewage Plant (behind AL-Nasige) in the city of Kut	15000000	16
M2	Maintenance of sewage station of Anwar Al-Sadr (behind Al-Karama Hospital) in the city of Kut	11000000	15
M3	Rehabilitation of the Al-Hoora sewage station in the city of Al-Kut	13300000	15
M4	Maintenance of station F2 in the city of AL-Kut	9400000	20
M5	Maintenance of station F7 in the city of AL-Kut	9300000	18
M6	Maintenance of submersible pumps in Wasit Sewerage Directorate	13000000	15
M7	Installing dry submersible pumps in Al- Shuwaija treatment plant	10500000	20
M8	Maintenance manholes of AL- Hay Al-Senai Street in the AL Hay district	14670000	20
M9	Cleaning manholes in Kut district	12000000	15
M10	Supplying electrical parts for district stations in Wasit Governorate	10500000	20
M11	Supplying mechanical parts for district stations in Wasit Governorate	13000000	15
M12	Maintenance and rehabilitation of AL-Fallahia sewage	15000000	18
M13	Supplying covers for road gullies of the AL-Kut sewage center	10680000	15
M14	Maintenance of the trunk line in the AL-Ezza AL-jededa area	12587000	15
M15	Supplying covers for the road gullies of the Al-Zubadia sewage center	11880000	15