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Artificial Neural Network Models to Predict the Cost and Time of Wastewater Projects

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ABSTRACT

Infrastructure, especially wastewater projects, plays an important role in the life of residential communities. Due to the increasing population growth, there is also a significant increase in residential and commercial facilities. This research aims to develop two models for predicting the cost and time of wastewater projects according to independent variables affecting them. These variables have been determined through a questionnaire distributed to 20 projects under construction in Al-Kut City/ Wasit Governorate/Iraq. The researcher used artificial neural network technology to develop the models. The results showed that the coefficient of correlation R between actual and predicted values were 99.4% and 99 %, MAPE was (26.24%), and (5.5%), and AA was (74%), and (94.5%), for cost and time model, respectively. The researcher concluded that the ANN model has a strong correlation and high accuracy, indicating that these models are characterized by high efficiency and good performance in predicting cost and time.

Keywords: Artificial neural network, wastewater projects, coefficient of correlation, mean absolute percentage error

نماذج الشبكة العصبية الاصطناعية للتنبؤ بكلفة ووقت مشاريع الصرف الصحي

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الخلاصة

تلعب البنية التحتية ، وخاصة مشاريع الصرف الصحي ، دورًا مهمًا في حياة المجتمعات السكنية ، كما أن هناك زيادة كبيرة في المرافق السكنية والتجارية بسبب النمو السكاني المتزايد. الهدف من هذا البحث هو تطوير نموذجين للتنبؤ بتكلفة ووقت مشاريع

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الصرف الصحي حسب المتغيرات المستقلة التي تؤثر عليها ، وقد تم تحديد هذه المتغيرات من خلال استبيان وزع على 20 مشروعا قيد الانشاء في مدينة الكوت / محافظة واسط / العراق. استخدم الباحث تقنية الشبكة العصبية الاصطناعية لتطوير النماذج.حيث أظهرت النتائج أن معامل الارتباط بين القيم الفعلية والمتوقعة كانت (99.4٪)، (% 99)،ونسبة الخطا المطلق MAPEكانت (26,24%) (% 5.5)،ودرجة الدقه AAكانت 74% ، (94.5٪) لكل من نموذجي الكلفة والوقت على التوالي.استنتج الباحث ان نماذج الشبكه العصبيه الاصطناعيه لها معامل ارتباط عالي واقل نسبة خطا وهذا يدل على ان النماذج تمتاز بكفاءه عاليه واداء جيد للتنبؤ بالكلفه والوقت.

الكلمات الرئيسية: تقنية الشبكة العصبية الاصطناعية, مشاريع الصرف الصحي, معامل الارتباط, نسبة الخطا المطلق

1. INTRODUCTION

The estimation team gives the construction cost and time great importance among the other management item **(Al-Zwainy, 2016)**. A good construction estimation is one of the most important factors for the success of construction projects. Many factors affect estimating the costs and duration of construction projects, which the researcher summarized by collecting workers' opinions on wastewater projects under construction in Wasit Governorate/Iraq. The experience of contractors and similar completed works can be considered an indicator of cost and time prediction, but it cannot be relied upon. There are several methods and techniques based on a scientific basis that have been developed to predict costs and durations for future projects. Modern forecasting methods are very valuable, such as artificial neural networks (ANN) developed based on artificial intelligence, which provides an alternative approach to cost and time estimation. This research aims to highlight the process of estimating the cost and time of wastewater projects in project management. The objective of efficiency the project management is to bring the project to achievement on schedule and cost. The accuracy of the schedule and budget of projects depends on the accuracy of those estimations **(Mohammed, 2015)**.

The study of **(Al -Saadi et al., 2017)** aimed to develop a mathematical model to predict the duration of road projects. Historical information was adopted on (99) projects from the period 2000 to 2017. The data collection was adopted from Road and Bridge Directorate/Wasit Governorate, and many independent variables were identified and used as input to the program. ANN technique was used to develop the model. The result shows the coefficient of correlation(R) between the planned value and the actual value is (90.6%), minimized testing error is (3.2%), and MAPE and AA were found to be (25.73 %) and (74.27%) respectively.

The purpose of (**Al-Zwainy, and Aidan, 2017**) study was to use modern technology such as ANN to predict the cost of construction projects. The data was collected from the Road and Bridge Directorate in the Republic of Iraq. This study used the ANN to develop a model to predict the cost of infrastructure projects. The result shows the coefficient of correlation between actual cost and predicted cost was (90.02%), and the degree of accuracy was (93.13%).

The main objective of **(Altaie and Borhan, 2018)** study is to develop a mathematical model to predict the duration of construction projects in Iraq. Historical data was adopted from (65) projects, and (13) independent variable was identified as input to the program. ANN technique was used to develop the model. The result shows the coefficient of correlation between the observed and predicted value is (89.9%), and the testing error is (1.51%). It concluded the ANN model is in a very agreement with actual values.

In 2020 the study of **(Waheeb et al., 2020)** aimed to identify the factor affecting the cost and duration of construction projects in emergency conditions and after a disaster. (30) projects in different areas in Iraq were selected as a case study, and questionnaire forms were distributed. ANN approach was used to develop a mathematical model to predict the changes in cost and time before starting the project. The results show the most important factors lead to schedule delay and cost increases that are redesigning of designs/plans, change orders, security issues, selection of low-price bids, weather factors, and owner failures.

The study of **(Peško et al., 2013)** aimed to estimate the preliminary cost and duration of the project. ANN approach was used to develop the model. The result showed the ANN model gives high accuracy.

(Vahdani, et al, 2016) aimed to build a prediction model based on a new neuro-fuzzy algorithm for estimating time in construction projects. The construction project is investigated to demonstrate the use and capabilities of the proposed model to see how it allows users and experts to interact actively and, consequently, make use of their own experience and knowledge in the estimation process. The proposed model is also compared to the well-known intelligent model (i.e., BPNN) to illustrate its performance in the construction industry.

2. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) are mathematical techniques designed to simulate biological neurons present in the human brain when a specific. It is a necessary treatment, and the main concept of artificial nervous networks is that they are a system for data processing consisting of a large number of units called neurons or nodes and interlocking in a high form with each other and having the same characteristic.

In the nerve cells in the human brain, where these neurons are connected to each other, the means of balanced links pass by signs from one neuron to another, where each neuron receives a number of inputs through its tangles. Still, it does not produce more than one sign of the outputs and transmits the expression of the outputs through the link to the nerves. **Fig. 1** shows a simplified model of biological neurological cells in the human brain **(Shaban, 2009)**.

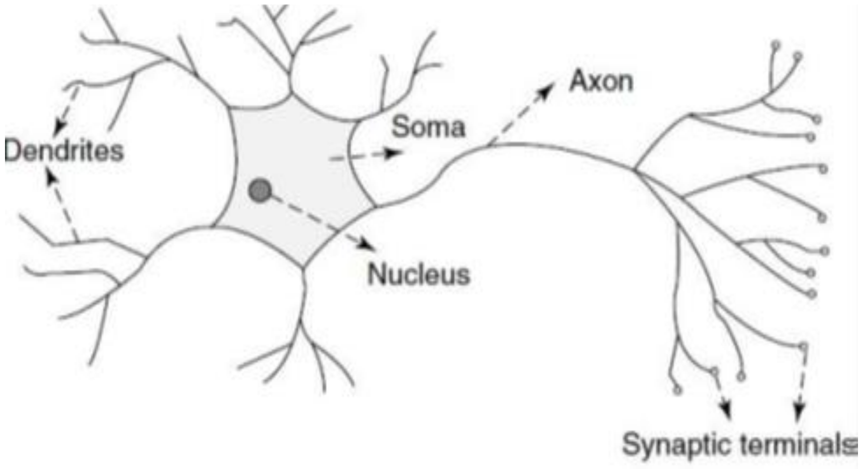

Figure1. Biological nervous network **(Sharma et al., 2012)**

3. DEVELOPMENT OF ANN MODEL

Many programs contain the ANN technique, such as (MATLAB), (NEUFRAM V.4) and (SPSS) programs; the researcher used the SPSS program V.20 in the development of the model because of characterized ease of use, which contains many options that have an important role in results analysis, and it has sensitivity analysis of independent variables. In order to design and develop of ANN model, the following steps have been followed.

3.1 Variables Identifications

The researcher identifies the independent variables based on (20) projects as a research sample, as shown in Appendix A, **Table (A-1)**. **Tables 1** and **2**. illustrate the details of the variables information.

Table 1. Input variables of ANN in the cost model

Variable	Description	Unit
X_1	Years	2011, 2012, …..etc
X_2	Project delivery system	1=DB, 2=DBB, 3=FA, 4= Turnkey
X_3	Type of finance	1= Region development 2=Operational plan 3= Investment plan, 4= Social contribution
X_4	Number of pump station	No. of item
X_5	Length of network	Length (m.l)
X_6	Number of manholes	No. of item
X_7	Site condition	1= Good, 2= Moderate 3= Bad
X_8	Duration	No. of day

Table 2. Input variables of ANN in the time model

Variable	Description	Unit
V_1	Cost of project	IQD
V_2	Site condition	1=Good, 2= Moderate, 3=Bad
V_3	Security situation	1= Good, 2= Moderate, 3=Bad
V_4	Length of network	Length (M.L)
V_5	Type of network	1= Rain, 2= Sewage, 3= Combined
V_6	Type of PDS	1= DB, 2= DBB, 3=F.A, 4= Turnkey
V_7	Performance and level of the company	1=Good, 2= Moderate, 3= Bad

3.2 Entering the variables

After identifying the independent variables, the data was entered for each project, as shown in Appendix (A), **Tables (A-2),** and **(A-3)**. The researcher used a multilayer perceptron, which is one of the most commonly used. This network, known as a feed-forward network, has supervised learning and the learning algorithm that uses its known backpropagation algorithm.

3.3 Data Division

The data division is classified into three sets, training, testing, and holdout, in order to assess the network efficiency by the maximum coefficient of correlation and least testing error. The beast data division is (70%) for training and (30%) for testing.

3.4 Data Training

The learning algorithm that is used in training is known backpropagation algorithm. In this algorithm, the weights have been controlled and updated in order to obtain the best weights and least error between actual and predicted output. When implementing this algorithm, two main stages follow feed-forward: no modification of weights and backpropagation. A batch training method was used.

4. RESULTS AND DISCUSSION

The results include the structure and performance of the network. The cost model contains 8 nodes in the input layer, and 1 node in each hidden and output layer, while the time model includes 7 nodes in the input layer, 4 nodes in the hidden layer, and 1 node in the output layer, as shown in **Fig. 2** and **3**, respectively.

Figure 2. Architect of ANN in the cost model

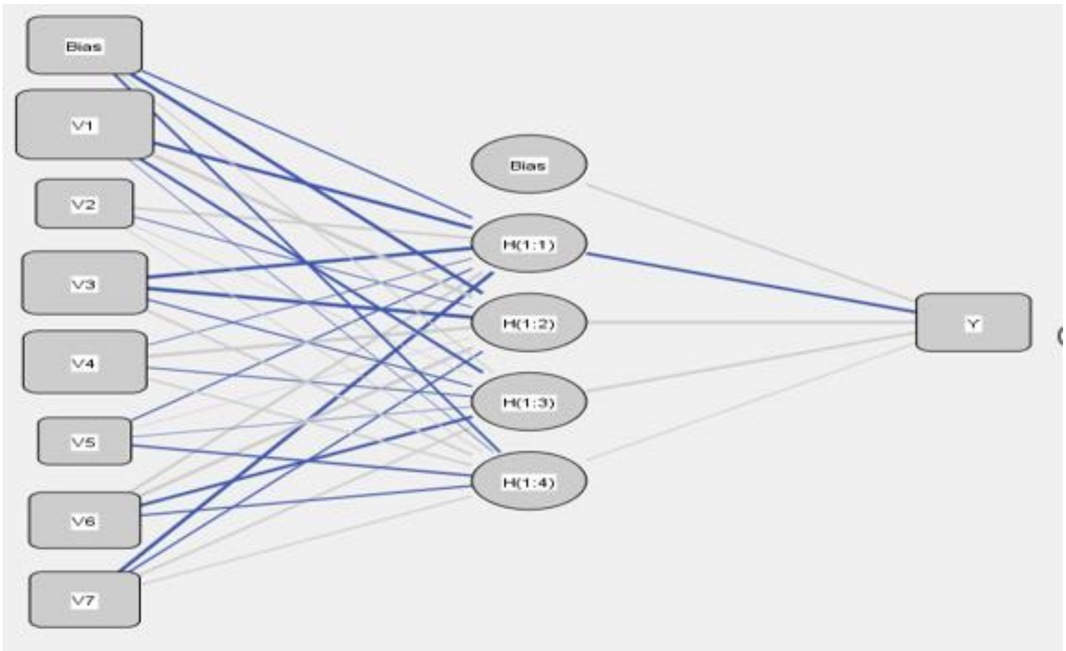

Figure 3. Architect of ANN in the time model

The layers in the network are linked by connection weights. The training stage has calculated and controlled these weights depending on data division, which considers the optimal weights that give the best and most accurate output. **Tables 3** and **4** illustrate the weights that have been controlled and connected between nodes from the input layer to the hidden layer and then the output layer.

Table 3. Connection weights of ANN in the cost model

Predictor		Predicted	
		Hidden Layer 1	Output Layer
		H (1:1)	Y
Input Layer	(Bias)	-1.808	
	X1	-.448	
	X2	1.000	
	X3	.877	
	X4	.727	
	X5	.182	
	X6	-.468	
	X7	-.142	
	X8	.335	
Hidden Layer 1	(Bias)		1.443
	H (1:1)		1.936

Tangent activation function was used to formulate the final equation of the cost model, as shown in equations 1 and 2.

$$P.C = \frac{1-e^{-[1.443+WT*tang(z)]}}{1+e^{-[1.443+WT*\tan g(z)]}} \qquad (1)$$

Where:

P.C: Predict cost , W = 1.936, T: Matrix converter

$$Z = Bias + W_{81} * X_{81} \qquad (2)$$

Where:

$$Bias = [1.808], \qquad W_{81} = \begin{bmatrix} -.488 \\ 1.000 \\ .877 \\ .727 \\ .182 \\ -.468 \\ -.142 \\ .335 \end{bmatrix}, \quad X_{81} = \begin{bmatrix} X1 \\ X2 \\ X3 \\ X4 \\ X5 \\ X6 \\ X7 \\ X8 \end{bmatrix}$$

Table 4. Connection weights of ANN in the time model

Predictor		Predicted				
		Hidden Layer 1				Output Layer
		H (1:1)	H (1:2)	H (1:3)	H (1:4)	Y
Input Layer	(Bias)	-.303	-1.291	.103	-.329	
	V1	-1.488	1.810	-.505	-.003	
	V2	.518	-.096	.054	.092	
	V3	-2.086	-2.287	-.237	.475	
	V4	-.062	1.777	-.149	.334	
	V5	-.195	.037	-.014	-.450	
	V6	.496	1.390	-.811	-.303	
	V7	-.947	-.240	.343	.266	
Hidden Layer 1	(Bias)					.469
	H (1:1)					-.628
	H (1:2)					1.197
	H (1:3)					.535
	H (1:4)					.140

Tang activation function was used to formulate the final equation of the time model as shown in equations 3 and 4.

$$P.T = \frac{1 - e^{-[0.469 + WT * \tan(X)]}}{1 + e^{-[0.469 + WT * \tan(X)]}} \quad (3)$$

Where:

P.T: Predicted time, $W = \begin{bmatrix} -0.628 \\ 1.197 \\ 0.535 \\ 0.140 \end{bmatrix}$, T: Matrix converter

$$X = Bias + W_{74} * V_{71} \quad (4)$$

$$\text{Bias} = \begin{bmatrix} -.303 \\ -1.291 \\ .103 \\ -.329 \end{bmatrix} \;,\; W_{74} = \begin{bmatrix} -1.488 & 1.810 & -.505 & -.003 \\ .518 & -.096 & .054 & .092 \\ -2.086 & -2.287 & -.237 & .475 \\ -.062 & 1.777 & -.149 & .334 \\ -.195 & .037 & -.014 & -.450 \\ .496 & 1.390 & -.811 & -.303 \\ -.947 & -.240 & .343 & .266 \end{bmatrix} ,\; V_{71} = \begin{bmatrix} V1 \\ V2 \\ V3 \\ V4 \\ V5 \\ V6 \\ V7 \end{bmatrix}$$

5. VERIFICATION OF ANN MODEL

The coefficient of correlation R between predicted and actual cost was determined to check the verification of the model. **Fig. 4** indicates the model's good performance because it has a strong correlation of 9.4 %, and **Fig. 5** shows the ANN model coefficient of determination. Thus, the researcher concluded that the values predicted by the model agree with actual measurements.

	X1	X2	X3	X4	X5	X6	X7	X8	Y	MLP_PredictedValue
1	2020	2	1	0	1856	38	1	365	.395	.611
2	2019	2	1	0	2235	21	1	400	.350	.845
3	2021	2	1	0	4564	92	1	600	.466	.807
4	2019	2	1	2	12906	250	1	500	17.933	18.033
5	2019	2	1	0	5270	106	1	600	.800	1.163
6	2021	2	1	1	24994	848	2	540	9.735	9.415
7	2013	2	1	0	33230	607	2	600	4.501	2.093
8	2013	2	1	1	8849	177	2	700	3.365	3.098
9	2013	2	1	1	32830	657	2	1260	22.350	22.325
10	2011	2	1	2	37555	1017	2	570	13.417	13.510
11	2022	2	1	0	6650	149	2	540	1.250	1.323
12	2011	1	3	2	8800	150	2	730	17.500	17.445
13	2012	2	3	13	236	4520	2	1065	147.422	120.869
14	2013	2	3	1	0	0	1	900	111.290	111.131
15	2019	2	1	1	130	2	2	400	3.512	3.385
16	2021	1	4	0	14412	337	2	360	1.665	1.170
17	2021	1	4	0	8601	159	2	360	1.142	1.219
18	2021	1	4	0	4535	124	2	365	2.212	1.220
19	2021	2	1	0	10840	261	2	365	1.573	1.227
20	2021	2	1	1	14743	203	3	540	9.477	8.080

Figure 4. Verification of ANN in the cost model

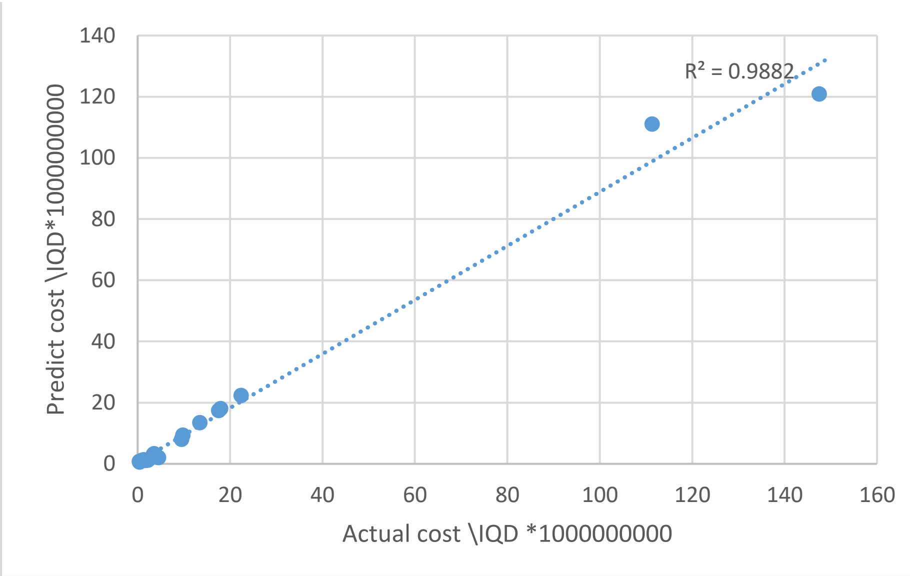

Figure 5. Comparing actual and predicted cost

The coefficient of correlation R between prediction and actual time was determined to verify the time model. **Fig. 6** indicates good performance of the model because it has a strong correlation R by 99 %, and Fig. 7 shows the ANN model has a coefficient of determination R2 of 98.1%. Thus, the researcher concluded that the values predicted by the model its agreement with actual measurements.

time model.sav [DataSet1] - IBM SPSS Statistics Data Editor

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1 : MLP_PredictedValu... 445.62677181327797

	V1	V2	V3	V4	V5	V6	V7	Y	MLP_PredictedValue_J
1	.395	1	2	1856	1	2	2	365	446
2	.350	1	1	2235	3	2	2	400	425
3	.466	1	1	4564	1	2	1	600	570
4	17.933	1	2	12906	2	2	2	500	520
5	.800	1	1	5270	3	2	2	600	565
6	9.735	2	2	24994	3	2	1	540	574
7	4.501	2	3	33230	3	2	3	600	610
8	3.365	2	3	8849	2	2	3	700	653
9	22.350	2	2	32830	3	2	3	1260	1202
10	13.417	2	3	37555	3	2	3	570	604
11	1.250	2	1	6650	3	2	2	540	592
12	17.500	2	2	8800	3	1	2	730	707
13	147.422	2	2	236	3	2	2	1065	1054
14	111.290	1	2	0	0	2	2	900	921
15	3.512	2	1	130	2	2	2	400	355
16	1.665	2	1	14412	3	1	2	360	385
17	1.142	2	1	8601	3	1	2	360	372
18	2.212	2	1	4535	3	1	2	365	368
19	1.573	2	2	10840	3	2	2	365	353
20	9.477	3	3	14743	1	2	2	540	539

Figure 6. Verification of ANN in the time model

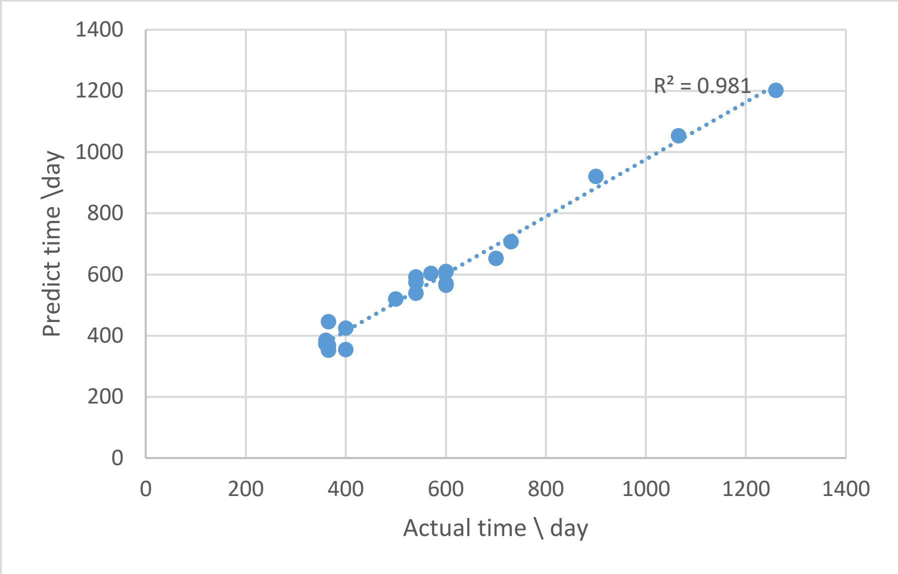

Figure 7. Comparing actual and predicted time

6. VALIDATION OF ANN MODEL

According to **(Abd et al., 2019)** and **(Almusawi and Burhan, 2020),** the statistical measures shown in **Tables (5)** and **(6)** is 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 (R^2)

Table5. Validation of ANN in the cost model

Description	Results %
MPE	- 6.5
MAPE	26.24
AA	74
R	99.4
R^2	98.8

Table 6. Validation of ANN in the time model

Description	Results%
R	99
R^2	98.1
MAPE	5.5
AA	94.5

7. SENSITIVITY ANALYSIS

The importance analysis, or sensitivity analysis, plays an important role in specifying the importance of each independent variable that effect on cost and time of wastewater projects, the variable (Type of finance X3) is most important by (100%) in effect on the cost of projects, while the variable (Site condition X7) is least importance as shown in **Fig. 8**. The sensitivity analysis of time model shows the variable (Cost of project V1) is most important by (100%) and (Type of network V5) is less important, as shown in **Fig. 9,** respectively.

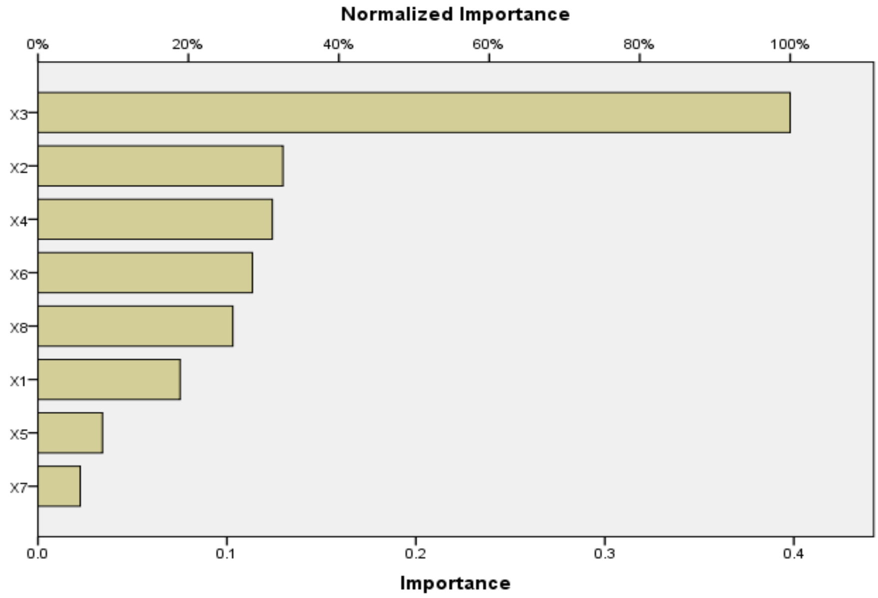

Figure 8. Importance analysis of ANN in the cost model

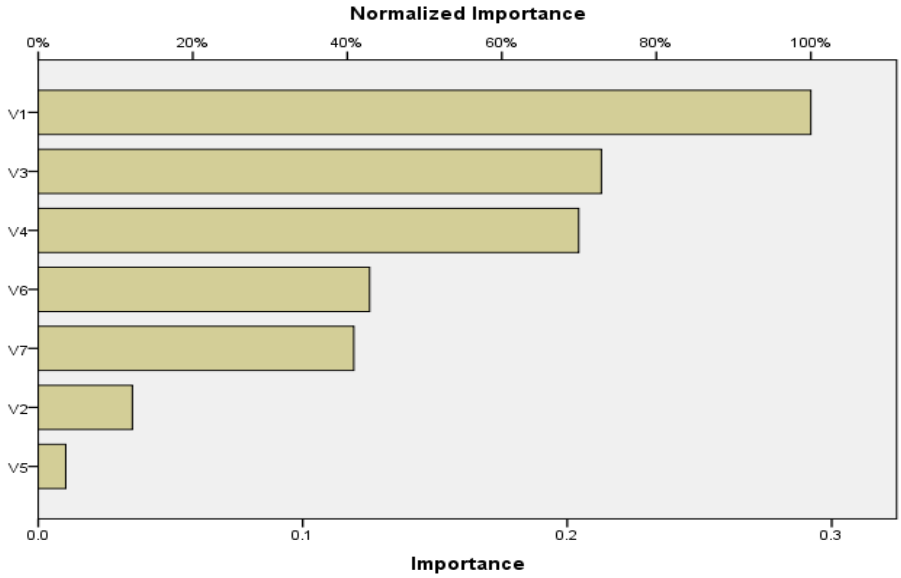

Figure 9. Variables importance analysis of the time model

5. CONCLUSIONS

The main objective of this research is to use a new technique known as the ANN model to estimate the optimum cost and time of wastewater projects in the field of project management in Al-Kut City/Wasit Governorate in Iraq. The application of ANN as a new method in project management was necessary to ensure project management's success. Two models were developed to predict the cost and time of wastewater projects. In this research, multilayered networks were used in the post-error propagation approach. It was found that the average accuracy (AA%) for the cost and time models has excellent predictability by (74%) and (94.5%), respectively. These models have strong coefficients of correlation (R) and less percentage error. This indicates that the ANN model's predicted values agree with actual values. The most important factor in the cost model was the type of finance X3, while project cost factor V1 was the most important in the time model.

REFERENCES

Abd, A.,M., Jasim, N.,A., Naseef, F.,S., 2019. Predicting the Final Cost of Iraqi Construction Project Using Artificial Neural Network (ANN), *Indian Journal of Science and Technology*, 12(28).

Al-Musawi, N. O. A., 2016. Application of Artificial Neural Network for Predicting Iron Concentration in the Location of Al-Wahda Water Treatment Plant in Baghdad City, *Journal of Engineering, 22(9)*, pp. 72–82.

Almusawi, H., T., and Burhan, A., M., 2020. Developing a Model to Estimate the Productivity of Ready Mixed Concrete Batch Plant, *Journal of Engineering, 26(10)*, pp. 80-93.

Al-Saadi, A., M., Zamiem,S., KH., Al-Jumaili, L., A., Jubair, M., and Al- Hashemi, H., A. 2017. Estimating the Optimum Duration of Road Projects Using Neural Network Model, *International Journal of Engineering andTechnology (IJET)*, 9 (5).

Altaie, M., and Borhan, A., M., 2018. Using Neural Network Model to Estimate the Optimum Time for Repetitive Construction Projects in Iraq, *Association of Arab Universities Journal of Engineering Sciences*, 5 (25), pp. 100-114.

Attal, A., 2010. Development of Neural Network Models for Prediction of Highway Construction Cost and Project Duration, M.Sc. thesis presented to the Faculty of the Russ College of Engineering and Technology of Ohio University.

Al-Zwainy, F. M., and Amer, R., 2016. Investigation Cost Deviation of Highway Project, *Research Journal of Applied Sciences, Engineering and Technology*, 13(11), pp. 843-855.

AL-Zwainy, F., M., and Aidan, I., A., 2017. Forecasting the Cost of Structure of Infrastructure Projects Utilizing Artificial Neural Network Model (Highway Projects as Case Study, *Indian Journal of Science and Technology*, 10 (20), pp. 1-12.

Mohammed, I., A., Mohsen, D., S., and Al-Zwainy, F., M., 2015. Earned Value Management in Construction Project, LAP LAMBERT Academic Publishing, Germany.

Peško, I., Trivunić,M., Cirović,G., and Mučenski, V., 2013. A Preliminary Estimate of Time and Cost in Urban Road Construction Using Neural Networks, *Preliminarna procjena vremena i troškova izgradnje gradskih prometnica primjenom neuronskih mreža* ,20(3), pp., 563- 570.

Shaban, K., El-Hag, A., and Matveev, A., 2009. A Cascade of Artificial Neural Networks to Predict Transformers Oil Parameters, *IEEE Transactions on Dielectrics and Electrical Insulation,* 16(2).

Sharma, V., Rai, S., and Dev, A., 2012. A Comprehensive Study of Artificial Neural Networks, *International Journal of Advanced Research in Computer Science and Software Engineering*, 2(10), pp. 278-284.

Singh, D. K., Thakur E. S, Kesharwani, S, Zadgaonkar, A., S., 2014. Analysis of Generated Harmonics Due to Single Phase PWM AC Drives Load on Power System Using Artificial Neural Network, *International Journal of Advanced Research in Engineering and Technology (IJARET)*, 5(2), pp. 173-185.

Vahdani, B., Mousavi, S., M., Mousakhani, M., Hashemi, H., 2016. Time Prediction Using a Neuro-Fuzzy Model for Projects in the Construction Industry, *Journal of Optimization in Industrial Engineering,* 19, pp., 97-103.

Waheeb, R., A., Andersen, B., and Suhili, R., 2020. Using ANN in Emergency Reconstruction Projects Post Disaster, *International Journal of Engineering Business Management*, 20(1), pp. 1-21.

Appendix A

Table A-1. Research sample

Code	Project name
P_1	Development of Al-Suwaira entrance from the side (Baghdad - Hilla) with a length of 1840 m for the two main sides and a design width of 46 m in the district of Suwaira (first phase)
P_2	Implementation of sewage and rain network and construction of separate streets in Sheikh Saad district
P_3	Developing part of the Rumaila and Dibiya neighborhood in the Al-Kut district
P_4	Implementation of sewage network and sewage station of Al-Janeb Al -Aymen in Al-Kut district
P_5	Implementation of a water network with the implementation of communications works with the development and rehabilitation of the electrical network with the implementation of a rain and sewage network with the development of scattered streets in the Mardan neighborhood in the Taj Al-Din district
P_6	Implementation of rain and sewage network and pump station in Al-Kafat street and rehabilitation of sewage network of the seventh complex
P_7	Development of the Al-Maimoun neighborhood and part of the 150 districts in the Al-Kut district
P_8	Implementation and rehabilitation of a water network and implementation sewage networks, a station, and a track line with the improvement of the electrical network in the Al Dubad, Al Huria, and Hay Al-Senay Street by a length of 21100 m
P_9	Developing the Al-Hawra neighborhood starting from Al-Shirazi Street to Alwa Al-Mawashi Street, including the parallel street to the Dujaili River, from the end of Al-Izza Street to the end of the borders of the Al-Hawra neighborhood, including Al-Madras Street with a total length of 44000 m.
P_{10}	Developing, paving streets, and rehabilitating the gardens of the Hay Al-Jihad neighborhood, with a total length of 20000 m in the city of Kut.
P_{11}	Completion of the design, supply, implementation, and operation of the Numaniyah sewage networks
P_{12}	Design, supply, implementation, and operation of Azizia sewage networks
P_{13}	Supplying and implementing a treatment plant, rain sewage networks, and lifting stations / the first phase of the city of AL-Suwaira (Chinese company CGGC)
P_{14}	Implementation pump station and sewage network in the Al-Ameer neighborhood
P_{15}	Implementation pump station and sewage network in the Al-Ameer neighborhood
P_{16}	Implementation of a rain and sewage network in the Al-Zahraa neighborhood/Jassan district

P_{17}	Implementation of a rain and sewage network in the Al-Abbas neighborhood/Jassan district
P_{18}	Implementation of a rain and sewage network for the northern entrance of Jassan
P_{19}	Design and implementation rain and sewage network of Al-Ameer in the Al-Zubadia neighborhood
P_{20}	Development and paving of street (Kut-Missan) length 6KM. and implementation trunk line for rainwater and lift station in Al-Kut

Table A-2. Input variables of the cost model

Code	X1	X2	X3	X4	X5	X6	X7	X8	X9	Actual cost/Billion IQD
P_1	2020	2	1	0	1856	38	1	7	365	.395
P_2	2019	2	1	0	2235	21	1	6	400	.350
P_3	2021	2	1	0	4564	92	1	1	600	.466
P_4	2019	2	1	2	12906	250	1	1	500	17.933
P_5	2019	2	1	0	5270	106	1	7	600	.800
P_6	2021	2	1	1	24994	848	2	1	540	9.735
P_7	2013	2	1	0	33230	607	2	1	600	4.501
P_8	2013	2	1	1	8849	177	2	1	700	3.365
P_9	2013	2	1	1	32830	657	2	1	1260	22.350
P_{10}	2011	2	1	2	37555	1017	2	1	570	13.417
P_{11}	2022	2	1	0	6650	149	2	2	540	1.250
P_{12}	2011	1	3	2	8800	150	2	5	730	17.500
P_{13}	2012	2	3	13	236	4520	2	7	1065	147.422
P_{14}	2013	2	3	1	0	0	1	8	900	111.290
P_{15}	2019	2	1	1	130	2	2	3	400	3.512
P_{16}	2021	1	4	0	14412	337	2	4	360	1.665
P_{17}	2021	1	4	0	8601	159	2	4	360	1.142
P_{18}	2021	1	4	0	4535	124	2	4	365	2.212
P_{19}	2021	2	1	0	10840	261	2	9	365	1.573
P_{20}	2021	2	1	1	14743	203	3	1	540	9.477

Table A-3. Input variables of the time model

Code	V1	V2	V3	V4	V5	V6	V7	Actual time /day
P_1	.395	1	2	1856	1	2	2	365
P_2	.350	1	1	2235	3	2	2	400
P_3	.466	1	1	4564	1	2	1	600
P_4	17.933	1	2	12906	2	2	2	500
P5	.800	1	1	5270	3	2	2	600
P_6	9.735	2	2	24994	3	2	1	540
P_7	4.501	2	3	33230	3	2	3	600
P_8	3.365	2	3	8849	2	2	3	700
P_9	22.350	2	2	32830	3	2	3	1260
P_{10}	13.417	2	3	37555	3	2	3	570
P_{11}	1.250	2	1	6650	3	2	2	540
P_{12}	17.500	2	2	8800	3	1	2	730
P_{13}	147.422	2	2	236	3	2	2	1065
P_{14}	111.290	1	2	0	0	2	2	900
P_{15}	3.512	2	1	130	2	2	2	400
P_{16}	1.665	2	1	14412	3	1	2	360
P_{17}	1.142	2	1	8601	3	1	2	360
P_{18}	2.212	2	1	4535	3	1	2	365
P_{19}	1.573	2	2	10840	3	2	2	365
P_{20}	9.477	3	3	14743	1	2	2	540