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BUILDING A MODEL FOR PREDICTING PRODUCTIVITY AND EVALUATING FACTORS AFFECTING PRODUCTIVITY BY USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Construction productivity is the main indicator of the performance of construction projects for any country. The productivity of construction projects is defined as the output of the system for each unit of input. The main objective of this paper is to identify and analyze factors affecting labor productivity in construction projects in Iraq through a closed questionnaire. While the second objective of this study is to construct a mathematical model for predicting the construction productivity for Formwork columns works. As well as, the assessment of factors affecting productivity using sensitivity analysis (Garson algorithm). After distributing, gathering and analysis the questionnaire and finding the relatve importance index (RII%) using the Likert scale for each influencing factor, the top ten factors were determined that effect on the productivity rate. As these factors are independent inputs of the model and affect the one output "dependent" is productivity rate. These factors are classified on the basis of the values of the relative importance index (RII%) calculated for each factor. Finally, the data were used in artificial neural networks (ANN) development of the prediction model. It was found that (ANN) have the ability to predict the Total productivity rate for formwork columns works for building project with a good degree of accuracy of the coefficient of correlation (R) was (94.39%) and average accuracy percentage of (AA%) was (85.45%). While, The sensitivity analysis indicated the following, The (V6) (Lack of labor surveillance) is ranked first with a relative importance of (27.61%). Contrast, The (V5) (The Ganger experience) has a low importance in the model with a relative importance around (0.35%) and it is ranked eleven.

Keywords: *Influencing factors, Relative Important Index, Artificial Neural Networks, labor productivity, Iraq.*

I. INTRODUCTION

The construction sector is one of the largest and most difficult industries in the world, and the human resources operating in the construction sector has a strategic role to increase the productivity of any construction company. Production is one of the most important factors affecting the general performance of any company working in the construction industry, whether small or Large size. Therefore, The standard value of output rate is the most major information used to analyze the performance of project labor productivity[1]. Drop in productivity has greatest influence and effect on overall productivity of the construction industry[2]. It is constantly dropping over a decade due to the shortage of standard productivity measurement method and the lack of understanding of various factors influencing labor productivity. In addition, there is a number of factors that directly affect the productivity of the work, and therefore it is important to study and identify the most important factors affecting the productivity of work to improve productivity.

II. RESEARCH OBJECTIVE

The aim of this paper is to highlight the importance of the use of modern technologies, And this is achieved through:

- Identification and analysis of the factors affecting the labor productivity as well as, the selection of the top ten factors affecting the productivity of work
- Building a model to predict or estimate the labor productivity of the formwork of the concrete columns by using (ANN).

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- Evaluating of Factors Influencing on labor productivity Using Sensitivity Analysis Technique (Garson Technique).

III. RESEARCH JUSTIFICATION

The motivations behind the research can be summarized as follows:

- Lack of previous studies on the influencing factors and their impact on the productivity of workers
- The application of (ANN) as a modern technology in the construction sector in Iraq has become an urgent necessity to ensure the success of construction projects.
- The lack of local studies on the subject of predicting the production of concrete works in construction projects using (ANN).
- There is a clear weakness in predicting the productivity of the construction works in the construction sector in Iraq due to the use of old methods that suffer from poor accuracy, speed and unreliability.
- Lack of documentation of actual productivity rates for previously completed construction projects.

IV. RESEARCH HYPOTHESIS

Motivation by above mentioned points, the following hypothesis is formulated: "There is a weakness in the methods used in predicting construction productivity in the construction sector in Iraq, and a lack of accuracy, speed and reliability. Consequently, there is a need to use modern methods and techniques for the purpose of forecasting the productivity in construction projects based on models of high accuracy and simplicity and simplicity of use"

V. THEORETICAL PART

1. Concept of productivity

Productivity is a major concern of any profit oriented organization as representing the effective and efficient conversion of resources into marketable products and determining business profitability [3]. Some productivity definitions also originated from special interest groups such as economists, industrialists, trade unions and politicians. Individuals or groups have meanings that fit their situation. For example, [4], defined labor productivity as the “ratio of the input in terms of labor hours to the output in terms of units of work”. [5] defined productivity as "a quotient obtained by dividing output by one of the factors of production. In this way it is possible to speak of the productivity of capital".

2. Productivity in construction

Construction productivity is a very important aspect and mostly analyzed because it is one of the main indicators of the performance of the construction industry. Relying on the engineering analogy of efficiency, productivity is defined as: [6]. The productivity measurement level of any company or project offers external and internal benchmarks for evaluation with projects or company standards [7,8].

3. Factors influencing labor productivity

Over the years, the factors affecting construction productivity rates have been thesubject of inquiry by researchers [5]. In order to increasing and improving productivity. The frequencies and importance of these factors affect varies from one country to another, and from one project to another. Several approaches have been adopted in relation to the classification of factors affecting construction productivity rates. Understanding the various important factors that affecting the productivity cost of both the positive and negative factors can be used to prepare a well-known strategy to reduce its consistencies. It is also used to improve the effectiveness of performance in a project. Knowledge and understanding are the various factors that affect the productivity of construction labor. It is also necessary to focus on the necessary steps to reduce the project cost overrun and the delay in project completion.

4. Artificial Neural Networks (ANN)

Neural networks are defined as the science that studies mathematical methods that can be formulated based on the simulation of biological cells in living organisms. Neurons are characterized by high speed in data processing and

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are able to learn and deal with different types of data, some of which may be faulty, making them suitable for many applications such as image recognition, speech processing, voice recognition, etc. Artificial neural network is a structure with parallel information structures. This structure consists of processing units that process the information called neurons or account elements. The signals pass between the neurons via connected lines, and each neuronal cell represents a local memory, and each line is connected to a specific numerical weight that strikes with the signals entering the neuron and then applies to each neuron a function that activates the network input, which is the sum of the weighted input signals for which the output signal is determined [9,10,11]. Figure (1) shows a model of an artificial neuron [12]. So, artificial neural networks are similar to the human brain because they gain knowledge of training and store this knowledge by using connecting forces within the neurons called tangential weights. There is also bio physiology, which gives biologists the opportunity to rely on understanding the evolution of biophysics [13].

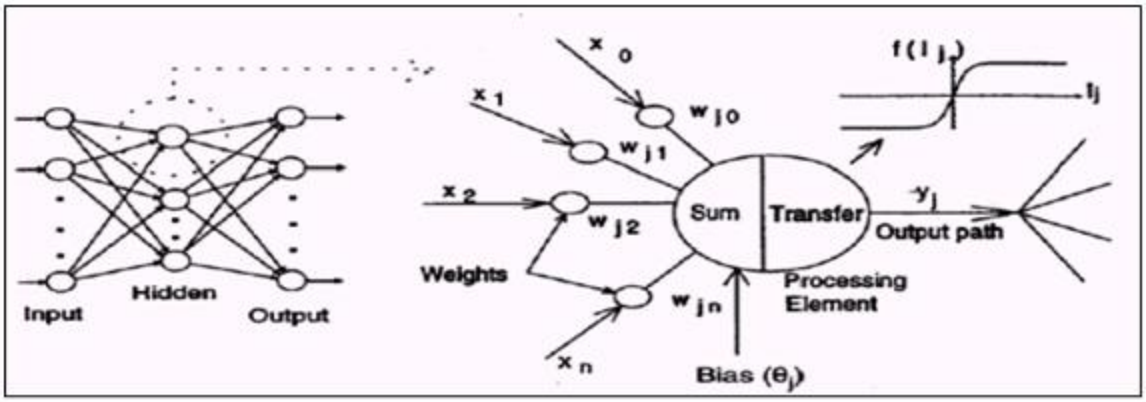

Figure 1: Typical structure and operation of ANNs (Shahin 2003).

VI. PRACTICAL PART

1. Identifying and Analyzing the factors influencing labor productivity

The methodology used in this paper is to determine the various factors that affect the productivity of formwork for columns concrete. The survey offers (20) influential factors in productivity, which have been collected from previous relevant research, review and revision by the participants in the initial pilot questionnaire.

Identifying and Analyzing the factors influencing labor productivity

The questionnaire included two sections: the first section includes general information about the participants. Also, it includes specialization, current work, years of experience, academic qualifications and the Guild degree and the replies to the questionnaire. The second section includes nine tables which represent the nine groups of factors influencing the productivity of labor and the scale dish Likert quintet in the design of the questionnaire [14]. This scale extends from the (1 very low) to (5 very high). To determine the structure of the questionnaire, a second assessment has been conducted (after a pilot questionnaire) after review and audit to ensure its effectiveness and suitability for construction projects in Iraq. The original questionnaire consists of 20 factors affecting labor productivity in construction projects in Iraq. Before distributing the questionnaire, a pilot test (pilot study) has been conducted to ensure that the questionnaire was designed gradually and appropriately simpler. The researcher presented questions in the questionnaire are presented in six of arbitrators (degree experts) engineer for the purpose of benefiting from their expertise in making the necessary revisions to the final version of the questionnaire.

Sample size

The sample respondents are engineers who work as: operational director, project manager, project coordinator, construction manager, site manager, site engineer, superintendent, estimator, supervisor, etc. They work at contractor companies in Iraq, both private and government. To get a statistically representative sample of the target, using equations (1), (2) have been used by many researchers, including [15] inter alia.

n=m/(1+((m-1)/N)) (1)

The m=Sample size of the population is not limited,
N= Sample size from a limited populationTo find the value of (m) using equation (2).

m=(Z^2*p*(1-p))/E^2 (2)

Whereas:
(Z) = the level of confidence (for example, 2.92, 1.575, and 2.245 represents the values of the confidence levels, which represent, 99%, 95% and 90% respectively),
(P) = degree of contrast between the target sample elements (0.5),
(*E*) = choice for point of maximum error.

Using a confidence level of 95% and the level of significance at 5% when the sample size is not specified, the estimated value (m) is attained by the clear application of the equation No. (2) as Follows:
m=(〖(1.96)〗^2*0.50*(1-0.50))/〖(0.05)〗^2 ≈ 385

Data collection

The sample targets engineers who work in the public and private sectors and in various administrative fields who manage projects, the project manager, supervising engineer, design engineer, within 100 engineer (N=100). So the required sample size to appropriate can be calculated by the applying the equation (1) as follows:
n=385/(1+((385-1)/100)) ≈79

Through collecting and analyzing the answers to the closed questionnaire, the responses of nine respondents were excluded and only 70 responses were analyzed for the questionnaire due to a lack of response to the questionnaire and a lack of interest by respondents in the questionnaire. To analyze the data, using the likert scale is used according to the following equation in (3), [16,17]:This section should be typed in character size 10pt Times New Roman, Justified.

RII(100%)=(5*(n5)+4*(n4)+3*(n3)+2*(n2)+1*(n1))/(5*(n1+n2+n3+n4+n5))………(3)

Where: n1, n2, n3, n4 and n5 = the number of respondents who selected: n1=little effect, n2=some effect, n3=average effect, n4=high effect, n5=very high effect. Table (1) shows the degree of significance of the factors affecting productivity through the scale shown in the table (1) when applying the five-dimensional Likert scale.

Table 1. Evaluation scale for affecting factors

≤ 20 SE < 40	40≤ AE < 60	60≤ HE < 80	80 ≤ VHE ≤100
Some Effect (SE)	Average Effect (AE)	High Effect (HE)	Very High Effect (VHE)

Measuring the consistency of the questionnaire

Stability is defined as the stability of the scale and lack of contradiction with itself, meaning that the measure would be re-applied to the same sample over a period of time and render the same results. The value of consistency should be between the two values zero and one [18]. In the questionnaire. Chronbach's alpha value is (0.96) which is a high-scale (Excellent). Therefore, it ensures the reliability and validity of each group in the questionnaire. Table (2) shows the reliability and validity for all factors.

Table 2. The reliability and validity statistics

Factors Affect Group	No. of Factors	Reliability	Validity
Total Factors Affect Group	20	0.96	0.98

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The most influential factors in the labor productivity

The relative importance index and ranking of all investigated 20 factors that might affect labor productivity in the construction sector in Iraq are listed in Appendix (1). Table (3) shows that the top eleven important factors affecting labor productivity in public and private construction projects in Iraq of engineers working in the construction sector.

Table 3. The eleven factors which affect labor productivity

Rank	Factors Affect	RII %	Degree of Effect
1	Availability of Material	**88.571**	Very High Effect
2	Weather changes	**88.00**	Very High Effect
3	Religious occasions	**86.286**	Very High Effect
4	Number of working groups	**86.00**	Very High Effect
5	Ganger experiences	**85.714**	Very High Effect
6	Lack of Workforce surveillance	**84.86**	Very High Effect
7	Ganger age	**84.00**	Very High Effect
8	Working at high place	**82.00**	Very High Effect
9	Drawings and specifications alteration during execution	**81.69**	Very High Effect
10	Sequence of floor	**80.571**	Very High Effect
11	Used Formwork type	**80.00**	Very High Effect

Eleven independent variables were collected from analyzing the factors influencing labor productivity. These independent variables shown in Table (4) can be classified into two types: objective based variables and subjective based variables. The objective variables can be measured based on the unit of measurement such that the age is measured in terms of years, experience is measured in terms of years and the floor height is measured in terms of meters. The subjective variables can be measured depending on the coding system proposed in other articles.

Table 4. The objective and subjective independent variable

Variable	Unit	Category of data	Code
Availability of Material	Low quantity= 1 Medium quantity= 2 High quantity= 3	Subjective (Quality data)	**V1**
Weather changes	Cold = 1, Hot = 2, Moderate=3	Subjective (Quality data)	**V2**
Religious occasions	High occasions=1 Medium occasion=2 Low occasion=3	Subjective (Quality data)	**V3**
Number of working groups	Number (1=one team, 2=two, team, … ele)	Objective (Quantity data)	**V4**
Workforce experiences	No. of Years	Objective (Quantity data)	**V5**
Lack of Workforce surveillance	Low surveillance=1 Medium surveillance=2 High surveillance=3	Subjective (Quality data)	**V6**
Workforce age	No. Years	Objective (Quantity data)	**V7**
Working at high place	Meter	Objective (Quantity data)	**V8**
Drawings and specifications alteration during execution	High alteration = 1 Medium alteration = 2 Low alteration= 3	Subjective (Quality data)	**V9**
Sequence of floor	Number ($1=1^{st}$, $2=2^{st}$, … ele)	Subjective (Quality data)	**V10**
Used Formwork type	Wood = 1, Iron =2	Subjective (Quality data)	**V11**

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Field data collection

The data for this study were collected from construction projects in Iraq, it included the activity Formwork for all (dependent and independent) variables for concrete column. The researcher has obtained (36) samples of observation for Columns Formwork. Then the analyzed them statistically according to statistical rules. Table (5) illustrates the summary of statistical analyses. The details of these data have been taken for accurate measurement of on-site construction productivity in Iraq.

Table 5. The descriptive statistics of the data

No. of Sample	Column Formwork												
	Statistical Parameters	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	Y*
N=36	Max	3	3	3	2	30	3	45	13.5	3	4	2	3.45
	Min	1	1	1	1	9	1	28	0	1	0	1	1.01
	Range	2	2	2	1	21	2	17	13.5	2	4	1	2.44
	Mean	2.53	2.03	2.22	1.50	18.25	1.89	37.89	6.69	2.22	1.94	1.44	2.18
	S.D	0.56	0.74	0.87	0.51	6.99	0.78	5.00	4.49	0.80	1.37	0.50	0.68

Y* = represents the productivity rate of the formwork for concrete column.

2. Building a model for neural networks

The methodology used to construct a synthetic neural network model developed in this research involves the development of a total of sub-models, such as input model, output model, data division model, network model, weight model, learning rate model, momentum term model, and Validation model."Neuframe-v.4" program was used to build the network, it is a commercial program written in the language (C++), This program is an artificial intelligence technology and easy to use in building artificial neural networks. Figure (2) shows the general Artificial Neural Network scheme of the Neuframe 4 program used to determine the relationship between independent variables as inputs and dependent variables as output. Except for the verification model, it was built using the statistical packages of social sciences (SPSS).

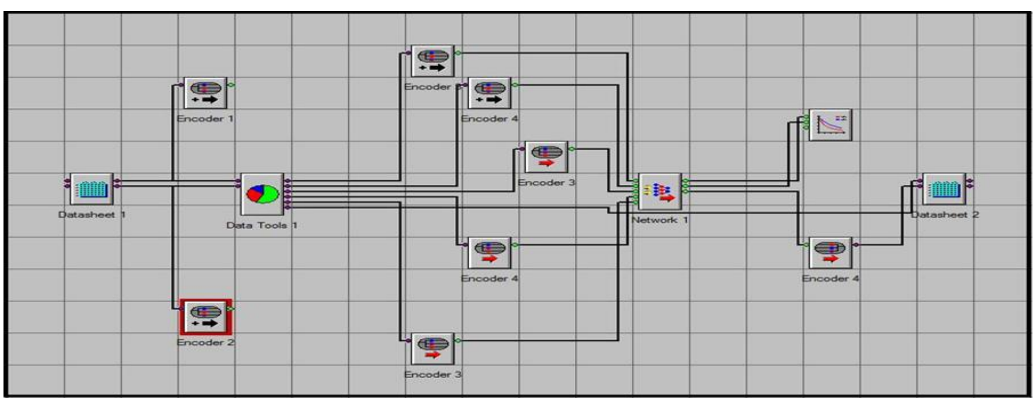

Figure 2. Graphing Component of NEUFRAME 4 Program.

Model inputs and outputs

The process of selecting variables in the input and output model is of great importance and contributes to improving the performance of the neural network, The increase in the number of input and output variables have a significant impact on the increase in the size of the neural network and lead to a decline in the speed of the learning process and thus affect the efficiency of the neural network. There are several ways to select the number of variables in a typical input and output, Priori of Knowledge method is adopted in this paper, as this method is widely used in the construction sector and is approved in many studies. This method can be used when there is no prior knowledge of input variables and their effect on output variables, Hence, the input model included independent variables, both quantitative and qualitative are: (V1) Availability of material, (V2) Climate status "weather changes", (V3) Religious occasions, (V4) Number of working groups, (V5) ganger experiences, (V6) Lack of workforce surveillance, (V7) ganger age, (V8) working at high place, (V9) Drawings and specifications alteration during execution, (V10) Sequence of floor, and (V11)Type of formwork used, The output model included the dependent variables productivity.

Data division model

Input or output data in the neural network are either continuous variables or separate variables, and these data are divided into three main groups: 1. training set. 2. testing set. 3. validation set. The training set is used to adjust the weights connected to the neural network, while the testing set is used to ensure network performance at different stages of education, The training is stopped when the error increases for the testing set, The validation set is used to assess the model performance once the neural network training has been successfully completed, Therefore, dividing the data into the three sets as above is a critical and important step in neural network modeling. In this paper, the method of statistically consistency is used for the purpose of dividing the data into the three groups (the training set, the testing group and the validation sit). This method ensures the statistical consistency of the data for each group, and ensures that there is no bias in dividing the data in each set using a test (T test) through the use of statistical standards namely the arithmetic mean, the standard deviation and range. Table (6) shows the division of data sets for training, testing and validation sets using the trial and error method, This paper uses different percentages of data for these groups in an attempt to obtain the best performance of the neural network by reaching the highest correlation coefficient to demonstrate the strength of the relationship between the neural network output (output predicted) and productivity measured (the actual), and in conjunction with less error testing ratio. These two criteria are adopted in this research to select the best division of data. The table (6) exhibits that the best division of data is (26) for set training, (6) for set validation and (4) for a test based on less error testing ratio (21.58%) and the largest correlation coefficient is (93.30%).

Table 6. The effect of data division in the performance of the network model.

Data Division			Training Error %	Testing Error %	Coefficient of Correlation (R) %	Coefficient of Determination (R^2) %
Training	Testing	Querying				
25	4	7	4.99	27.81	38.50	14.82
26	**4**	**6**	**4.94**	**21.58**	**93.30**	**87.05**
25	5	6	4.93	22.82	93.30	87.05
24	6	6	4.93	22.81	93.30	87.05
28	2	6	5.30	27.20	93.30	87.05
26	5	5	26.30	16.19	62.80	39.44
27	4	5	5.25	28.15	62.80	39.44
28	3	5	6.33	28.19	62.80	39.44
29	2	5	5.42	38.24	62.80	39.44
28	4	4	5.09	20.60	21.30	4.54
29	3	4	5.23	21.11	21.30	4.54
30	2	4	5.45	27.51	21.30	4.54
30	3	3	6.38	45.67	80.23	64.37
24	5	7	5.36	23.19	38.50	14.82
23	6	7	5.11	24.78	67.85	46.04
22	7	7	6.80	33.30	-38.51	14.83
21	8	7	5.69	29.33	-38.51	14.83
26	2	8	6.11	27.22	-54.99	30.24
25	3	8	5.56	25.18	-54.99	30.24
24	4	8	5.99	22.58	-54.99	30.24

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For the purpose of distributing the total data to the field variables, the (36) readings are divided into three sets, namely the training set and the testing set and validation set.

The Neuframe program used provides an efficient way to distribute the data in three Styles. They are given below:

- Random: In this method, the program randomly distributes variable data on the three totals and according to the percentages, as in table (6).
- Stripe: In this method, the program divides the total data into non-specific sets of packets, each packet contains data for the training set, the testing set and the validation set, and then the data for each set is collected from each package down to the percentages as in table (5).
- Blocked: In this mode, it is handled with the overall data as a package and divided respectively into the three sets. (26 set) of the first data are to ascribed as be set training set, and the second (4 set) are a testing set, third (6 set) and the final totals of the data are the validation set. The effect of the use of different options for dividing (Random, Stripe, Blocked) is verified and shown in the table (7). It can be observed that the best performance of the neural network is when using the (Blocked) method as it has the least error for the test (14.78%).
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Table 7. Effect of the division method on the performance of the neural network

Data Division %			Choices of division	Training error%	Testing error%	Coefficient correlation (R) %
Training	Testing	Querying				
26	4	6	Striped	4.94	21.58	93.30
26	**4**	**6**	**Blocked**	**5.62**	**14.78**	**92.40**
26	4	6	Random	6.25	18.54	-69.55

Neural network model

Artificial neural network architecture is the way in which neurons connect to each other to form a network. The determination of the appropriate number of neural nodes in the middle class of the neural network is an important factor for the success of the neural network, knowing that the number of nodes in the input layer is equal to the number of factors affecting the calculation of productivity. The output layer has one neuron node, which is the measured output. There are many methods that can be used to find the optimal number of neural nodes in neural networks[19]. The best way to use an equation (6) is to start by selecting one node in the middle layer and then starting with a gradual increase in the number of nodes until the best performance of the network and the maximum number of nodes equals (I+2I). This method is adopted in the present paper.

Max. No of Node = (1+2*I) (4)

Using the default parameters of the program used in this research, a Learning Rate and its value has been (0.2), and the momentum term has been valued (0.8). On the other hand, the transfer function for nodes, the output layer and the hidden middle layer are (Sigmoid). Figure (3) below shows that the highest coefficient of correlation is (97.63) and the lowest error rate is (12.75) when the hidden layer contains three nodes. So the typical form of this network developed in this research is three layers of neuron (Input layer, Hidden layer, Output layer). The actual processing of data is done in the hidden layer and the output layer is essential.

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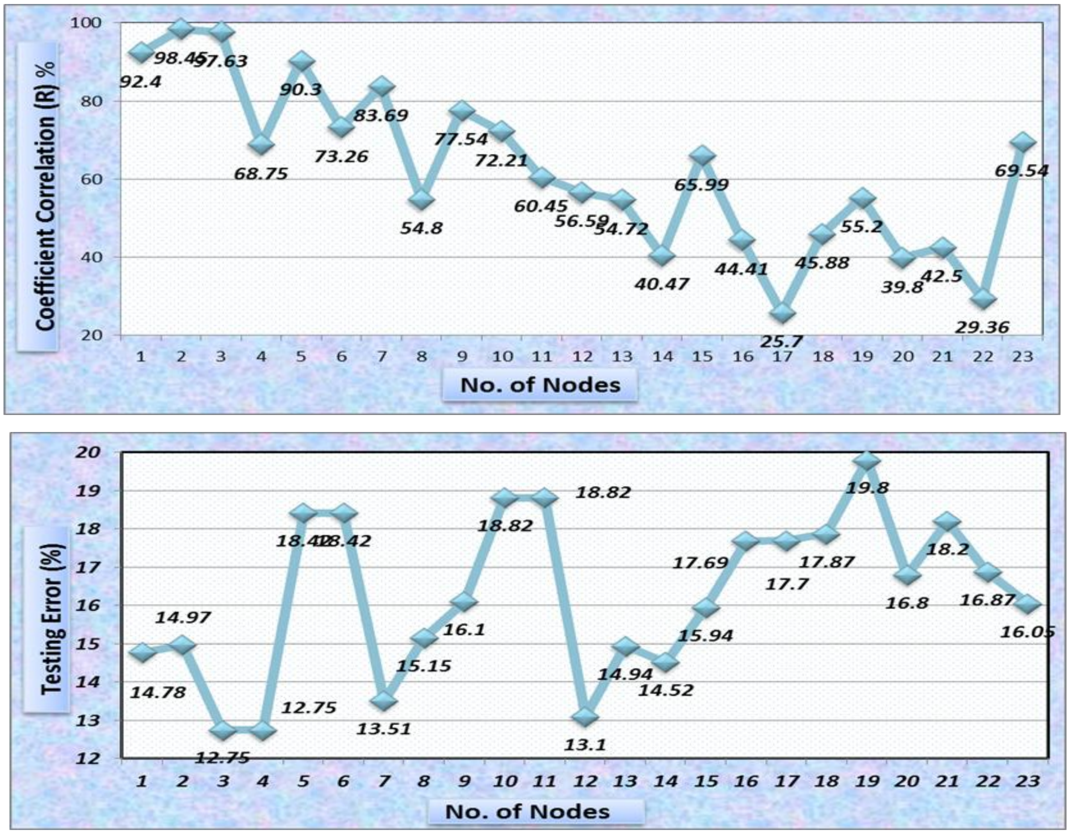

Figure 3. Performance of ANNs model with different hidden nodes (CFPR)

Momentum term & Learning rate

These models are important in improving the performance of the neural network, and they work together in a coherent way through the neural network architecture, and they both affect each other. A series of tests are conducted on the neural network by changing the Momentum Term to values ranging from the minimum parameter (0) to the upper limit (1). Table (8) shows that the network is not sensitive to the specific range of momentum (0.01 to 0.9) and then gradually begins to check the error. The best performance of the network when the momentum setting equals to (0.95%) has the lowest error rate of the testing set (12.75%). The largest correlation is (97.63%), and the training error is (5.10%), There is an improvement in the performance of the network as the momentum is set near the maximum limit (1).

Table 8. Effects Momentum Term on ANNs Performance (CFPR)

ParametersEffect	Momentum Term	Training Error %	Testing Error %	Coefficient Correlation (R) %
Model No. 2	0.01	5.39	12.75	97.63
Choices of division	0.05	5.31	12.75	97.63
(Blocked)	0.1	5.47	12.75	81.40
Learning Rate	0.2	5.42	12.75	97.63
0.2	0.3	5.36	12.75	97.63
No. of Nodes	0.4	5.54	12.75	97.63
3	0.5	5.40	12.75	97.63
Transfer function in hidden layer	0.6	5.17	12.75	97.63

(Sigmoid)	0.7	5.39	12.75	97.63
Transfer function in output layer	0.8	5.43	12.75	97.63
(Sigmoid)	0.9	5.32	12.75	97.63
	0.95	**5.10**	**12.75**	**97.63**

In addition, it is noticeable that the learning rate affects the performance of the model. The learning rate determines the speed of change of inclination and bias, and the learning rate effect is achieved when the optimal value of the momentum parameter is set to 0.95, as shown in table (8). Table (9) shows that the network is not sensitive to the specific range of momentum (0.15 to 0.8) and then gradually begins to test the error. The best performance of the network when the Learning setting equals to (0.1) and has the lowest error rate of the testing set (12.75%). The largest correlation is (97.63%), and the training error is (5.16%). There is an improvement in the performance of the network as the momentum sets near the maximum limit (0).

Table 9. Effects Learning rate on ANNs Performance (CFPR)

Parameters Effect	Learning Rate	Training Error %	Testing Error %	Coefficient Correlation (R) %
Model No. 1	0.01	5.85	12.75	97.63
Choices of division	0.02	5.29	12.75	97.63
(Blocked)	0.05	5.36	12.75	97.63
Momentum Term	**0.1**	**5.16**	**12.75**	**97.63**
0.95	0.15	5.49	12.75	80.80
No. of Nodes	0.2	5.56	12.75	97.63
3	0.3	5.46	12.75	97.63
Transfer functions inthe hidden layer	0.4	5.83	12.75	97.63
(Sigmoid)	0.5	5.53	12.75	97.63
Transfer function in output layer	0.6	5.34	12.75	80.13
(Sigmoid)	0.7	5.74	12.76	97.63
	0.8	5.60	12.76	97.63

In order to study the effect of the conversion function, four tests were performed as shown in Table (10) below. It can be observed that the performance of the neural network is almost non-sensitive to the type of function. The correlation coefficient is (97.63%) and the error rate is between (12.75%) and (12.91%).

The best performance of the network model was obtained by using the sigmoid function for both the intermediate, (Hidden Layer) and the output layer due to the highest correlation coefficient (97.63%) and the lowest percentage of the test (12.75%). It is commonly used as a conversion factor for neurons because it secures nonlinearity in network nerve calculations and intention by converting the value of the activation of the neuron within the domain [0,1].

In addition, it provides the additional advantage of the simplicity of its derivative required in the algorithm of the propagation of the back of errors, which is one of the learning algorithms monitored in the feeding front networks in this research.

Table 10. The effect of the Transfer Function on the performance of the neural network model.

Transfer Function		Training Error %	Testing Error %	Coefficient Correlation (R) %
Hidden Layer	Output Layer			
Sigmoid	Sigmoid	**5.10**	**12.75**	**97.63**
Sigmoid	Tanh	6.07	14.47	96.63
Tanh	Sigmoid	6.65	11.88	91.00
Tanh	Tanh	5.35	12.91	93.47

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Weight model

Each neuron and connection is characterized by a link to a value called weight, which is, how important the connection between these two elements is. The neurons multiply each input value from the previous layer neurons with the weight of the communication with these neurons, then multiply the multiplication outputs, and vary according to the type of neuron, The output of the transformation considers the output of the neuron which is transferred to the neurons of the subsequent layer. Consequently the network has been trained to obtain the values of weights for holding the hyphen between the first layer (input) and the second layer (middle or hidden) as well as the weights between the second layer and the third layer (output) as shown in Table (11).

Table 11.Adjust the weights between layers of the neural network

Hidden layer nodes	W_{ji} (weight from node i in the input layer to node j in the hidden layer)						Hidden layer threshold θ_j
	V1=1	**V2=2**	**V3=3**	**V4=4**	**V4=5**	**V5=6**	
Y1	0.947	0.627	-0.189	0.761	0.271	0.270	**0.3979**
	V7=7	**V8=8**	**V9=9**	**V10=10**	**V11=11**		
	-0.499	-0.471	0.514	-0.123	0.882		
Y2	**V1=1**	**V2=2**	**V3=3**	**V4=4**	**V5=5**	**V6=6**	**0.8611**
	0.152	-0.134	0.242	-0.720	0.173	-1.56	
	V7=7	**V8=8**	**V9=9**	**V10=10**	**V11=11**		
	-0.520	0.197	0.082	0.433	-0.263		
Y3	**V1=1**	**V2=2**	**V3=3**	**V4=4**	**V5=5**	**V6=6**	**-0.3263**
	0.186	-0.135	-0.093	-0.072	-0.142	-0.416	
	V7=7	**V8=8**	**V9=9**	**V10=10**	**V11=11**		
	-0.328	-0.397	-0.390	-0.237	0.0054		
Output layer nodes	W_{ji} (weight from node i in the hidden layer to node j in the output layer)						Output layer threshold θ_j
	V12=12	**V13=13**	**V14=14**	-	-	-	
Y4	2.81666	-4.5999	-0.9926	-	-	-	**0.09048**

$$CFPR = \frac{1}{1 + e^{(-0.09048 - 2.8167 * Tanh\,Y1 + 4.5999 * Tanh\,Y2 + 0.9926 * Tanh\,Y3)}} \quad (5)$$

Where:

It should be noted here that all inputs (variables) (V1, V2, V3, V4, V5, …V11) have been converted to standard values ranging from (0 , 1) as required by the program (Neuframe-v4) during the training period, to find the measured product through the equation (6), where the values will be between (0,1). In order to obtain the actual productivity values, the weights must be adjusted using equation (7) below, to return the values to their real value

Scaled Value=((X-Xmin))/((Xmax-Xmin)) (6)

Finally, the final form of the equation of productivity is as follows:

As:

$$CFPR = \frac{2.44}{1 + e^{(-0.09048 - 2.8167 * Tanh\,Y1 + 4.5999 * Tanh\,Y2 + 0.9926 * Tanh\,Y3)}} + 1.01 \quad (7)$$

And:

Y1= {-1.623+ (0.474* V_1) + (0.314* V_2) + (-0.094* V_3) + (0.761* V_4) + (-0.0129* V_5) + (0.135* V_6) + (-0.0294 * V_7) + (-0.0377* V_8) + (0.257* V_9) + (-0.0307 * V_{10}) + (0.8823* V_{11}) } ……….………… (8)

Y2= {3.236+ (0.076* V_1) + (-0.067* V_2) + (0.121* V_3) + (-0.72* V_4) + (0.0082* V_5) + (-0.7798* V_6) + (-0.0306 * V_7) + (0.0157* V_8) + (0.041* V_9) + (0.1083 * V_{10}) + (-0.263* V_{11}) } …....………………… (9)

Y3= {0.7652+ (0.093* V_1) + (-0.0676* V_2) + (-0.0466* V_3) + (-0.072* V_4) + (-0.0067* V_5) + (-0.2081* V_6) + (-0.0193 * V_7) + (-0.0318* V_8) + (-0.195* V_9) + (-0.059 * V_{10}) + (0.0054 * V_{11}) } …………….. (10)

Validation model

In table (12), it can be observed that the productivity rate for formwork column model performance is good through the verification stage because it presents a high correlation (R) value between the actual and predicted productivity which is (94.39%).

Table 12.Verification of Productivity rate for formwork column Model.

Obs.	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	A.P	E.P	Error
1	2	2	1	1	15	1	30	2.8	1	1	1	1.77	1.803	-0.033
2	2	2	1	2	30	1	40	12	1	3	1	2.15	2.959	-0.809
3	3	2	3	2	25	2	32	7.5	2	2	2	2.88	3.426	-0.546
4	2	2	1	1	18	1	32	12.5	1	4	1	1.36	1.370	-0.01
5	3	2	3	2	18	2	32	7.5	3	2	1	2.77	3.379	-0.609
6	3	2	3	2	18	3	40	7.5	3	2	2	3.25	3.449	-0.199
Correlation (R) between Actual & Estimate												**R=94.39 %**		

To evaluate the neural networks for formwork productivity rate model, the predicted values are plotted against the actual-values for data verification. Figure (4) shows the ability of Neural networks in the formwork productivity rate model. From this figure, it can be found that the R2=89.09% for 6 observations.

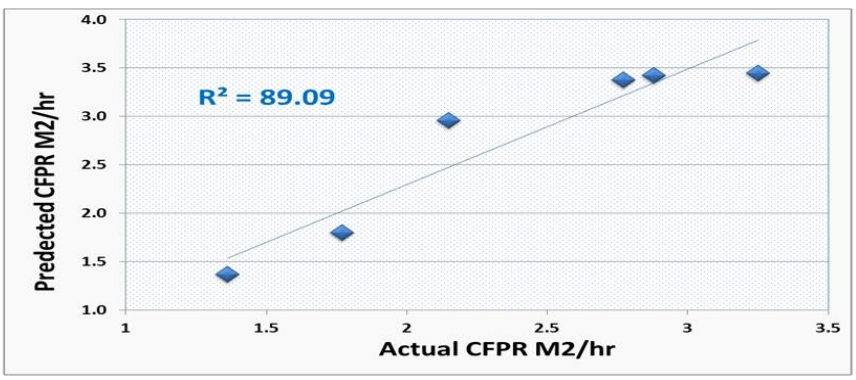

Figure 4. Comparison between Predicted and Actual Productivity for Verification Data

In this paper, the statistical criteria below are used to prove the efficiency of the equation derived from the artificial neural network model developed in this research

Mean Absolute Percentage Error (MAPE)

MAPE=(∑(│A-E│)/A*100%)/N (11)

Average Accuracy Percentage (AA%)

AA%= 100%-MAPE (12)

The Coefficient of Determination (R2)

The Coefficient of Correlation (R)

Where is:

A: Actual productivity values,

E: The values of the calculated productivity through the equation

N: Number of observations

Table (13) below shows the results of the four statistical criteria above. The results show that the equation can be used to predict the productivity in the neural network model and has a very high accuracy of 85.45%%, which is an excellent result for the efficiency of the model developed in this research.

Table 13. Result of the Comparative Study

Description	ANN for model CFPR
MAPE	14.55%
AA%	85.45%
R	94.39%
R2	89.09%

3. Sensitivity analysis of the ANN model input

In an attempt to identify which of the input variables (Independent) have the most significant influence on the output predictions, a sensitivity analysis is carried out on the Artificial Neural Network model. A simple and innovative technique proposed by Garson (1991) AS Mentioned in [12] is used to interpret the relative importance index of the input variables by testing the connection weights of the trained network. For a network with one hidden layer, the technique involves a process of partitioning the hidden output connection weights into components associated with each input node. Figure (5) shows the results of the sensitivity analysis of the model**.**

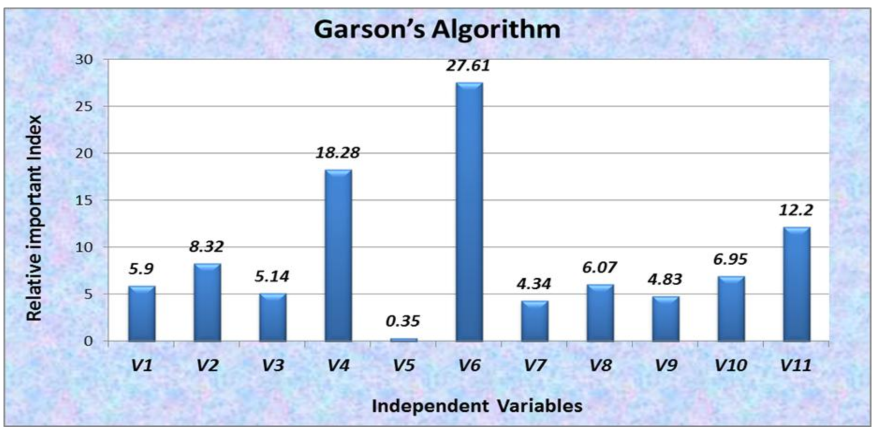

Figure 5. The results of the sensitivity analysis of the model

VII. CONCLUSION

Conclusions in the present research can be summarized in the following points:

- This study tried to identify and analyze the factors that affect labor productivity in construction projects in Iraq. It was found that ten factors negatively affect labor productivity. They are: (1) Availability of Material, (2) Climate status "Weather changes", (3) Religious occasions, (4) Number of working groups, (5) Ganger experiences, (6) Lack of Workforce surveillance, (7) Ganger age, (8) Working at a high place, (9) Drawings and specifications alteration during execution, (10) Sequence of the floor, and (11) Type of Formwork Used
- The main objective of this research is to use a method known as artificial neural networks to predict the productivity of concrete column blocks for building projects, The paper used the multi-layer neural network technology backward propagation of error. It is found that these networks had the ability to predict total productivity with an excellent degree of accuracy of (AA%=85.45%) and correlation coefficients (R= 94.39%). This model is relatively insensitive to the number of hidden nodes,
- The sensitivity analysis indicated the following:The (V6) (Lack of labor surveillance) is ranked first with a relative importance of (27.61%). It has the most significant effect on the predicted model. The (V4) (The number of working groups) is ranked second with relative importance (18.28%). The results also indicate that (V11) (The type of Formwork) is ranked third in relative importance (12.20%). The (V2) (Climate status (Weather)) has the

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forth relative importance (moderate importance) in the ANN model. The fifth rank is reserved for the (V10) (The Sequence of floors) in the ANN model. The (V8) (Working at high place) is ranked sixth with a relative importance (6.07%). The (V5) (The Ganger experience) has a low importance in the model with a relative importance around (0.35%) and it is ranked eleven.

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REFERENCES

1. *Z. Herbsman, R. Hulgeri,"Keyword Searching and Browsing in Databases using BANKS," Construction Management and Economics, 1990, vol. 8, no. 1, pp. 49..*
2. *M,Jiukun, Paul. Goodrum, andF, William. Maloney, "Construction Craft Workers' Perceptions of the Factors affecting their Productivity", ASCE 07339364, 2009 vol. 135, no. 3, pp. 217.*
3. *S,Wilcox.,B,Stringfellow., R, Harris., and B, Martin, "Management and productivity". Transportation research board, committee on management and productivity, 2000 Washington, USA*
4. *H Thomas. AndS, Sanders. R. "Comparison of labor productivity. Journal of Construction Engineering and Management", ASCE, 1992, 118(4), PP. 635- 650.*
5. *M, Lema. "Construction of labor productivity modeling". University of Dar Elsalaam Journal of Project Management, 1995, Vol. 16, no. 2, pp. 107-113*
6. *J, Michael,. and Q, Sami. "System Thinking and Construction Productivity", Joint research between Civil engineering, 2000 University of Nottingham U. K. Department of Civil Engineering and Architecture of University Bahrain.*
7. *S, Park, Hee., R, Thomas, Stephen. AndL, Tucker, Richard., "Benchmarking of Construction Productivity". Journal of Construction Engineering and management. 2005. Vol. 131, no. 7, p. 772-778. DOI 10.1061/(asce) 07339364 (2005)131:7 (772). American Society of Civil Engineers (ASCE).*
8. *D, Ellis., and S, Lee., "Measuring Project Level Productivity on Transportation Projects", Journal of Construction Engineering and Management. Vol. 132, no. 3, p. 314-320. DOI 10.1061/(asce)0733-9364 (2006)132:3(314). American Society of Civil Engineers (ASCE).*
9. *F, Luger., And A, stubble field,. "Artificial Intelligence structures andStrategies for complex problem solving ", Addison Wesley Longman, 1998, Inc., USA.*
10. *S, Haykin., "Neural Network a Comprehensive Foundation", 2nd Ed.Prentice-Hall International, 1999, Inc.*
11. *W, Kinnebrock. "Neural Networks Fumdoman tales, Application ‹ Example ", Galgotia publications, Prt. Ltd., 1995, New Delhi.*
12. *M, Shahin., "Use of Artificial Neural Networks for Predicting Settlement of Shallow Foundations on Cohesionless Soils", PH. D. Thesis, Department of Civil and Environmental Engineering, 2003. University of Adelaide.*
13. *F. Al-Zwainy."The Use of Artificial Neural Networks for Productivity Estimation of finishing Stone works for Building Projects". Journal of Engineering and Development,2012. 16 (2): 42-6.*
14. *S, Durdyev., And S, Ismail., " Pareto analysis of on-site productivity constraints and improvement techniques in construction industry", Scientific Research and Essays,2012. 7(4): 824-833.*
15. *R, Hogg., And E, Tannis,. "Probability and statistical inferences", 8th Ed., Prentice Hall, Upper Saddle River,2009, NJ.*
16. *I, Mahamid. A, Al-Ghonamy., And M, Aichouni, "Major Factors Influencing Employee Productivity in the KSA Public Construction Projects". International Journal of Civil & Environmental Engineering IJCEE-IJENS,2013. 14 (1): 16-20.*
17. *A, Enshassi. S, Mohamed., Z, Abu Mustafa,. And P, Mayer."Factors affecting labor productivity in building projects in the Gaza Strip", Journal of Civil Engineering and Management,2007. 13 (4): 245-254.*
18. *S, Abu Shaban. "Factors Affecting the Performance of Construction Projects in the Gaza Strip", MSc Thesis, Islamic University of Gaza, Construction Management Department,2008, Palestine.*
19. *F, Al-Zwainy."The Use of Artificial Neural Network for Estimating Total Cost of Highway Construction Projects", a thesis submitted to the Civil Engineering Department, College of Engineering, 2008, Baghdad University, Ph.D*