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Developing a Model to Estimate the Productivity of Ready Mixed Concrete Batch Plant

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ABSTRACT

Productivity estimating of ready mixed concrete batch plant is an essential tool for the successful completion of the construction process. It is defined as the output of the system per unit of time. Usually, the actual productivity values of construction equipment in the site are not consistent with the nominal ones. Therefore, it is necessary to make a comprehensive evaluation of the nominal productivity of equipment concerning the effected factors and then re-evaluate them according to the actual values.
In this paper, the forecasting system was employed is an Artificial Intelligence technique (AI). It is represented by Artificial Neural Network (ANN) to establish the predicted model to estimate wet ready mixed concrete (WRMC) plant production and dry ready mixed concrete (DRMC) plant production, in addition to determining the factors affecting productivity.
The results showed that the artificial intelligence neural network is an effective technique to estimate the productivity of the dry and wet ready mixed concrete batch plant. The ANN model showed satisfying results of validation for both training and external datasets with the range of training dataset and poor results with the data that exceeds the range of training. At the same time, the skills of the operators, frequent failure of concrete, and lack of construction materials were the most important factor that affected productivity.

Keywords: productivity, ready mixed concrete batch plant, Artificial Neural Network, construction projects.

تطوير نموذج لتخمين انتاجية الخباطة المركزية للخرسانة الجاهزة للخلط

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الخلاصة

يعد تخمين انتاجية الخباطة المركزية للخرسانة الجاهزة للخلط أداة أساسية لإنجاز عملية البناء بنجاح.حيث يتم تعريف الانتاجية على أنها ناتج النظام لكل وحدة زمنية. غالبا ما تكون القيم الإنتاجية الفعلية لمعدات البناء في الموقع غير متوافقة مع القيم

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الاسـمية. لذلك ، من الضـروري إجراء تقييم شـامل للإنتاجية الاسـمية للمعدات المتعلقة بالعوامل المتأثرة ثم إعادة تقييمها وفقًا للقيم الفعلية.

في هذا البحث ، تم استخدام نظام التنبؤ باستخدام تقنية الذكاء الاصطناعي (AI) والتي تمثلها الشبكة العصبية الاصطناعية (ANN) لإنشاء النموذج المتوقع لتقدير إنتاج مصنع الخرسانة الجاهزة الرطبة (WRMC) ومصنع إنتاج الخرسانة الجاهزة الجافة (DRMC) , بالاضافة الى تحديد العوامل التي اثرت في تقليل الانتاجية عما هو مصمم لها.

أظهرت النتائج إن الشبكة العصبية للذكاء الاصطناعي هي تقنية فعالة لتقدير إنتاجية مصنع خلط الخرسانة الجاهزة الجافة والرطبة عن طريق تقديم نموج تنبؤي للانتاجية و أظهر نموذج شبكة العصبية نتائج مرضية في الاختبار في كل من مجموعة التدريب ومجموعة البيانات الخارجية ضمن نطاق مجموعة البيانات التدريب والنتائج السيئة مع البيانات التي تتجاوز نطاق التدريب وأن مهارات المشغلين والفشل المتكرر للخرسانة ونقص مواد البناء كانت أهم العوامل التي أثرت على الإنتاجية.

كلمات الرئيسية: الانتاجية, مصنع الخلط للخرسانة الجاهزة للخلط, الشبكة العصبية الاصطناعية, مشاريع البناء

1. INTRODUCTION

Productivity is considered an important indicator that affects the selection of any equipment in construction projects. Construction equipment is one of the necessary resources of accomplishment and success of construction projects. Recently, contractors conduct more types of construction activities that require various types and sizes of equipment, and they usually invest the greatest value for the costs of a project specifically for the intensive projects. Equipment productivity plays the main role in estimating the time and cost of any construction project. The use of equipment includes increasing the rate of production, lowering the total cost, carrying out activities that cannot be carried out manually, maintaining the planned rate of production when there is a shortage of labor, maintaining high-quality standards, etc. Thus, the correct choice and use of equipment contribute to the quality, safety, economy, and completion of the project in a timely **(Sheikh, et al., 2016)**. Otherwise, delays in project implementation may happen because of incorrect selection of equipment, lack of equipment on time, wrong mechanization, and lack of technology. Researchers defined productivity in different ways according to the nature of the work; all agreed that productivity is the rate of outputs to inputs **(Productivity Commission Report, 2004)**. Productivity can be defined as a measure of converting resources of a firm, an individual, industry, or overall economy into, services, goods, and generates income.

The success of a construction project is highly connected to its machinery production **(Fan, et al. (2007)**, **(Tatari, and Skibniewski, 2006)**. Machinery manufacturers generally supply an ideal hourly output for their machines for users. This ideal hourly production is called hourly nominal output which is different from the actual hourly production of a machine in construction projects. Actual production depends mainly on the conditions of project sites. Estimation of actual production and hence the discrepancies between the nominal and actual production rate is an essential element in assessing the time and cost required to finish construction. To estimate production, it is very important to know how different project site conditions affect the production of machinery **(Peurifoy, et al., 2006).**

2. METHODOLOGY

One of the most important methodologies used to solve engineering problems is modeling. Many variables can be analyzed and modeled with similar data, and the results can be used in several applications (**Thamer, and Erzaij. K, 2018)**. In this paper, the forecasting system employed an Artificial Intelligence (AI) represented by Artificial Neural Network (ANN) to establish the predicted model of productivity to estimate wet ready mixed concrete (WRMC) plant production, and dry ready mixed concrete (DRMC) plant production.

In the field of evaluation an actual output of production and transferring the Ready Mixed Concrete (RMC) qualitative and quantitative research would be implemented to collect related data using;

1. Interviews with experts in the field study were achieved to gain an understanding of determinants and factors that affected productivity.
2. Observation and documentation to realize the observations and documentation, the researcher visited most of the central batch plants and recorded daily productivity and specification of the plant, which determine the actual productivity and factors that affected the nominal productivity.

2.1. Direct factors influencing the productivity

The factors involved in this context are based on actual data of batch plant conducted during observation and documentation processes of concrete production, daily report, plus expert opinion. All these data were evaluated using the plant's website. Generally, these data were classified into two categories. And all these categories were divided into sub-divisions that were used to estimate the productivity of the batch plant. However, main and sub-factors are summarized in the sections (2.1.1), and (2.1.2).

2.1.1. Loading duration factors

The factors involved in this category are specialists in the batch plant specifications and track mixer capacity, where only the effective factors were chosen. The researcher conducted that the loading duration determinants factors are directly related to the number of times of construction materials filling to track mixer in respect of dry ready mixed concrete and number times of loading the mixing unit of wet ready mixed concrete where the productivity increases by decreasing the number of loading. The effective factors are presented below:

1. Number times of cement filling (N_{cement}) are calculated based on cement weighing scale in the batch plant (M_{cement}), track mixer capacity (V_{track}), and cement content (Cc) in 1m^3 concrete using the **Eq. (1).**

$$Ncement = \frac{\mathrm{V}_{track^*}\,\mathrm{Cc}}{\mathrm{M_{cement}}} \tag{1}$$

2. Number times of aggregate filling ($N_{aggregate}$) are calculated based on aggregate weighing scale ($M_{aggregate}$), track mixer capacity (V_{track}), and aggregate content (Aw) in 1m^3 concrete using the **Eq. (2).**

$$N_{aggregate} = \frac{\mathrm{V}_{track^*}\,\mathrm{A}_w}{\mathrm{M_{aggregate}}} \tag{2}$$

3. Width of conveyor belt of aggregate (W_{belt}).

4. Power of motor for conveyor belt (PW_{belt}).
5. Number times of filling the mixing unit for one truck mixer (N_{mixer}) are calculated using track mixer capacity (V_{track}) and mixing unit capacity (V_{mixer}) utilizing the **Eq. (3)**.

$$N_{mixer} = \frac{V_{track}}{V_{mixer}} \tag{3}$$

The factors from (1 to 4) above were used in the dry batch plant productivity equation while, the factors from (3 to 5) were employed in the wet batch plant productivity model because of the mixing unit was not considered in the dry batch plant. Otherwise, the factors N_{cement} and $N_{aggregate}$ were neglected in wet ready mixed concrete (WRMC) production calculations because the weighing scale of batch plant for both cement and aggregate is more than the mixing unit.

2.1.2. Transferring duration factors

Transferring duration factors considered more critical than the others were five factors involved in this group; these factors are:

1. The distance between batch plant location and project site (D).
2. The speed of track mixer (Strack).
3. The traffic situation (T): classified into; uncrowded, moderate, and crowded.
4. The nature of road (Rroad); classified into; natural and hard road.
5. The number of track mixers (No. track mixers).

The results of collecting data in this context for both loading and transferring duration determinants factors would be investigated to establish the predicted model.

2.2. Artificial neural network (ANN)

Artificial neural networks (ANN) communication systems are computational systems inspired by biological neural networks that make up human minds. They are a form of (AI) that attempts to mimic the function of the human brain and nervous system **(Kriesel, D., 2005)**. Although the concept of ANNs was first introduced in 1943 by the neurophysiologist Warren McCulloch and the mathematician Walter Pitts, researches with applications of ANNs have blossomed during the introduction of the backpropagation training algorithm for a feed-forward multilayer perceptron in 1986. F**ig 1**. explains the natural neurons that represent the concept of ANNs.

Neural network models are algorithms used for cognitive tasks, such as learning and optimization, which are based on concepts derived from the researches into the nature of the brain. Models of artificial neural networks have been developed and used as an alternative to regression analysis since the propagation of the posterior propagation algorithm **(Akkol, S., 2015).** The presence of hidden nodes gives the neural network its ability to model any function associated with independent variables **(Mohammed. SR, et al., 2016)**

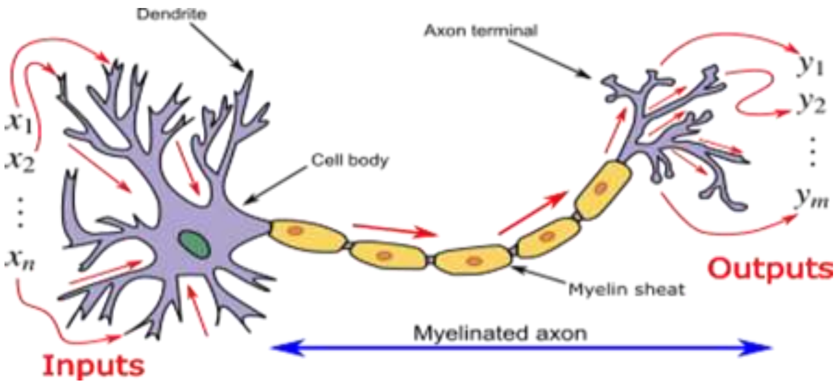

Figure 1. Natural neurons (ANN conception).

Generally, there are two types of ANNs tutorials, feedback, and feed-forward ANN. The feedback network feeds information back into itself, and it is well suited to solve optimization problems, while the feed-forward network transmits the information in a forward direction only.

A simple example of a neural network is shown in **Fig 2.**, consisting of an input layer, hidden layer, and output layer, all of them are connected with no feedback connections.

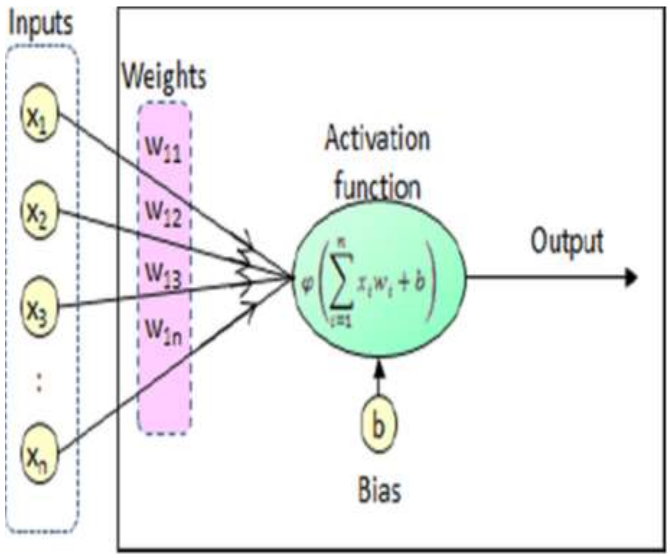

Figure 2. The basic structure of an ANN model.

The weighted sum of the inputs is transferred to the hidden neurons, where it is transformed using an activation function that can be defined as can affect how one has to format input data. The outputs of the hidden neurons, in turn, act as inputs to the output neuron where it undergoes another transformation. If the number of hidden neurons is small, the network may not have sufficient degrees of freedom to learn the process correctly (**Mustafa, A., 2015).** The output of a feed-forward neural network with one hidden layer and one output neural network is given by **Eq. (4)**.

$$Yt = f_o\left[\sum_{j=1}^{HN} WO_j * f_h\left(\sum_{i=1}^{m} WH_{ij} \, . \, X_{it} + b_j\right) + b_o\right] \quad (4)$$

Where Yt is the output, f_h , f_o are the hidden and the output neuron activation functions, HN is number of hidden neurons, WO_j is the weight of the link between the j^{th} hidden neuron and the output neuron, m is the number of input neurons, WH_{ij} is the weight of the link between the i^{th} input and the j^{th} hidden neuron, X_{it} are the inputs, b_j is the bias of the j^{th} hidden neurons, and b_o is the bias of the output neuron.

3.2. Indirect factors influencing the productivity

Choosing the influencing factors was according to the data gathered, which included interviews, observation, and documentation. These factors were classified into three types are; management, site, and factors related to the concrete batch plant itself, which are collected during interviewing and questionnaire processes.

Management factors comprised eleven factors that are concerned with the planning, scheduling, and skills of the management and supervisory staff. These Factors are; Operator's staff skills, poor management or supervision, communications between site staffs, quality control, incentive payments, good cooperation and coordination, regular progress control, supervisor performance, poor safety and accidents, concrete batch manager efficiency, batch plant operator efficiency, truck mixers drivers' efficiency, procurement plan efficiency, and misuse of schedule.

Site factors include eleven factors related to the location, nature, size of the project, availability of construction materials, and the impact of weather factors. However, these factors are; lack of material, nature of the project, size project, temperature effects, rain effects, working space availability, specifications requirement, feed aggregate bin, blow cement silo, frequent failure of concrete, and the project urbanity.

Factors related to concrete batch plant are; equipment breakdown, non-availability of fuel, spares not available, truck mixers efficiency, machines maintenance efficiency, the existence of automatic control mixing, number of cement silos, and age of the plant.

The gathering data would be analyzed using importance index, which is represented by (II) after converted the answers of the questionnaire to numerical data, as shown in **Table (1)**. However, Eq. (5) would be based on the ranking of factors according to importance index **(Singh, 2007)**

$$FI = \frac{\sum(fi \times pi)}{\sum(pi)} \quad ... \ (1 \le fi \le 5) \qquad (5)$$

where; FI: frequency weight (1, 2, 3, 4, or 5), Pi: number of participants who answered option i, The importance index (RII) for each factor is calculated from **Eq.** (6).

$$RII = \frac{FI}{A} * 100\ \% \qquad (6)$$

where; A = Highest weight (i.e., 5 in this case).

3. RESULTS

3.1. Results of the ANN model

The simulation of the neural network using NEUFRAME V.4 software was employed in this study that works underlying the mathematical formulas and supervised learning. The feedback network was investigated in this work. This network comprises three main components; input layer, hidden layer, and output layer. The input data and independent variables used in this network are classified into training, testing, and querying. The set of trial and error was adopted to obtain the optimum network. **Fig 3.** represents the final graphing component of ANN.

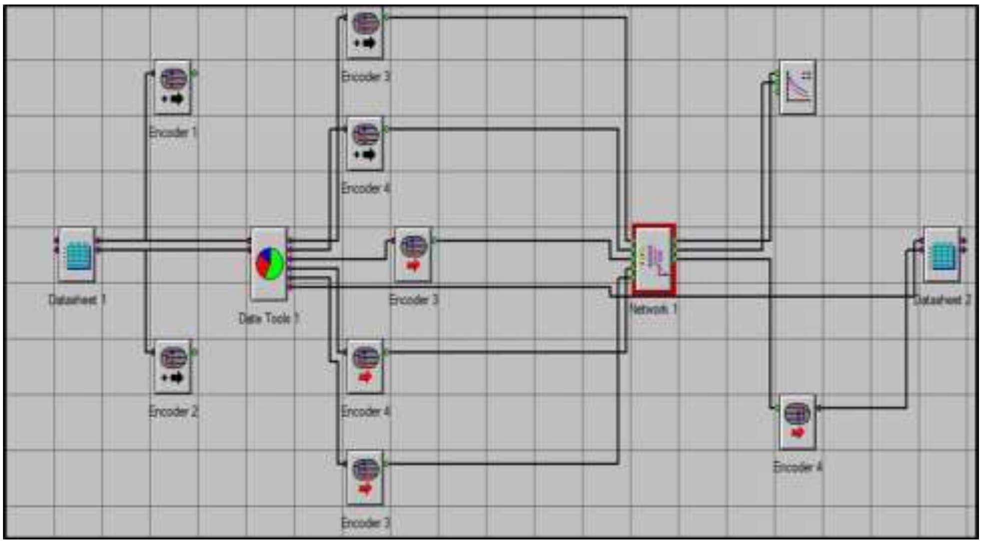

Figure 3. The graphing component of ANN.

The task of the input layer or datasheet component is the data input process that is used to establish the model and provides the storage of data within the workspace. **Fig. 4** shows the input dataset and output of the ready mixed concrete batch plant

Main input output

Main Sheet:Area (1,1)-(9,21) 1.2

All	A	B	C	D	E	F	G	H	I
1	1.20	30.00	2.00	2.00	5.00	70.00	1.00	10.00	105.00
2	1.20	30.00	6.00	6.00	9.00	70.00	3.00	10.00	90.00
3	0.80	17.50	1.00	4.00	10.00	40.00	1.00	5.00	60.00
4	0.80	17.50	5.00	8.00	12.00	40.00	3.00	5.00	51.60
5	0.70	15.00	1.00	3.00	2.00	40.00	1.00	3.00	60.00
6	0.70	15.00	6.00	6.00	4.00	40.00	3.00	3.00	52.80
7	0.60	12.00	2.00	3.00	0.50	10.00	1.00	4.00	45.00
8	0.60	12.00	6.00	6.00	3.00	10.00	3.00	4.00	39.60
9	0.50	8.00	20.00	9.00	15.00	20.00	2.00	3.00	20.00
10	0.50	8.00	20.00	9.00	15.00	20.00	2.00	10.00	28.00
11	1.00	22.00	4.00	3.00	2.00	30.00	2.00	3.00	80.00
12	1.00	22.00	8.00	6.00	2.00	30.00	2.00	3.00	70.00
13	1.00	22.00	1.00	3.00	5.00	40.00	1.00	8.00	85.00
14	1.00	22.00	1.00	3.00	5.00	40.00	1.00	8.00	85.00
15	1.00	18.00	4.00	4.00	1.80	60.00	2.00	4.00	82.00
16	0.80	22.00	2.00	3.00	16.00	60.00	1.00	10.00	65.00

Figure 4. The input data set.

After training the DRMC algorithm using ANN successfully and selecting the best data division at training, testing and querying values was equal to 52.38%, 4.76%, 42.86%, respectively, the optimal model of estimation the value of DRMC productivity is shown in the **Eq. (7)**.

$$DRMC\ Productivity = \frac{P_{Rang}}{1+e^{(-5.58tanhk+2.98)}} + Pmin \tag{7}$$

where:

- **P_{Range}:** the difference between maximum and minimum values of actual productivity used in training the network, which equals 85.
- **P_{min}**: minimum value of actual productivity used in training the network, which equals 20.

It should be noted that before using Equation (k), all the input variables should be scaled between (0.0) and (1.0) using the data ranges in the ANN model training and with the application of **Eq. 8**.

$$xn = \frac{x - xmin}{\mathrm{xmax} - \mathrm{xmin}} \tag{8}$$

Where x is the input variable.
xmax is the maximum value of the input variable
xmin is the minimum value of the input variable

$$\mathrm{k} = [-1.2 + 1.78\mathrm{Wbelt} + 0.042\mathrm{Pbelt} - 0.024\mathrm{Ncement} - 0.058\mathrm{Naggregate} - 0.024\mathrm{D} + 0.0068\mathrm{Strack} + 0.007\mathrm{T} + 0.0366\mathrm{No.track}] \tag{9}$$

5.1.1.1. Validation of DRMC Model using an external dataset

The validation of the DRMC model showed acceptable values for the correlation and poor error measurements, as shown summarized in **Tables 1.** and **2** and **Fig 5**.

Table 1. The actual and the predicted DRMC values of training data using ANN.

Case No.	Actual productivity	Predicted productivity
1	105	97.51
2	30	25.28
3	50	82.45
4	110	98.73
5	130	98.98
6	50	49.74
7	70	71.41

Table 2. The validation of the ANN model using DRMC dataset.

Performance measure	Validation set
Correlation coefficient	0.87
Mean absolute error (MAE)	12.66
Root mean squared error (RMSE)	17.82

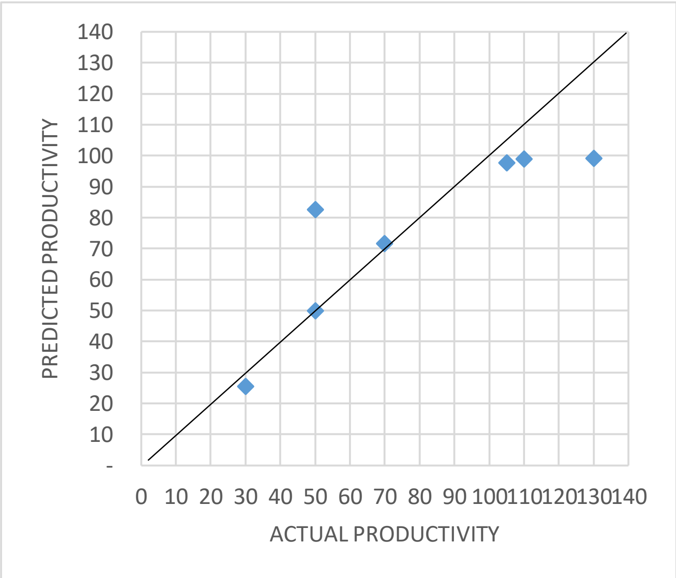

Figure 5. The actual and the predicted values of DRMC dataset using ANN.

The optimum from **Eq**. (**10**) of the wet ready mixed concrete (WRMC) productivity was a sigmoid transfer function type that was established during the training process of the artificial neural network (ANN), and data division was 56.25%, 6.25%, 37.5%.

$$\text{WRMC Productivity} = \frac{P_{Rang}}{1+e^{(-8.11\tanh k+4.14)}} + P_{min} \qquad (10)$$

where:

- P_{Range} is the difference between the maximum and the minimum values of the actual productivity used in training the network, which equals 70.
- P_{min} is the minimum value of the actual productivity used in training the network, which equals o 20.

Before using **Eq. (11)**, all the input variables should be scaled between (0.0) and (1.0) using data ranges in ANN model training and with the following **Eq. (11**).

$$xn = \frac{x-xmin}{xmax-xmin} \quad (11)$$

$$K = -0.54 - 0.28W_{belt} + 0.09P_{belt} + 0.025N_{mixer} - 0.076D - 0.003S_{track} - 0.063T + 0.117No.track \quad (12)$$

3.2.Validation of the WRMC Model using a dataset

The results of the performance and the validation of the WRMC model were divided into two fields. The first one shows a low correlation and high error parameters of the data that exceeded the range of the network. In respect to the second field, which comprised the data within the range of the network, the result showed a high correlation and acceptable values of error parameters, as shown in **Table 3.** and **4.** and **Fig 6.** that explains the comparison of the actual and the predicted productivity. In **Table 3**., the data in case no. 1 and 2 represent those that exceeded the range of the ANN network.

Table 3. The validation of the ANN model using WRMC dataset.

Performance measure	Validation set	
	with data that exceed the range of the network	without data that exceed the range of the network
Correlation coefficient	0.70	0.95
Mean absolute error (MAE)	25.04	10.42
Root mean squared error (RMSE)	36.23	12.22

Table 5. Actual and Predicted WRMC values of training data using the ANN model.

Case No.	Actual productivity	Predicted productivity
1	145	88.58
2	160	88.61
3	30	33.67
4	65	86.79

5	40	52.70
6	60	73.03
7	80	88.14
8	85	88.16

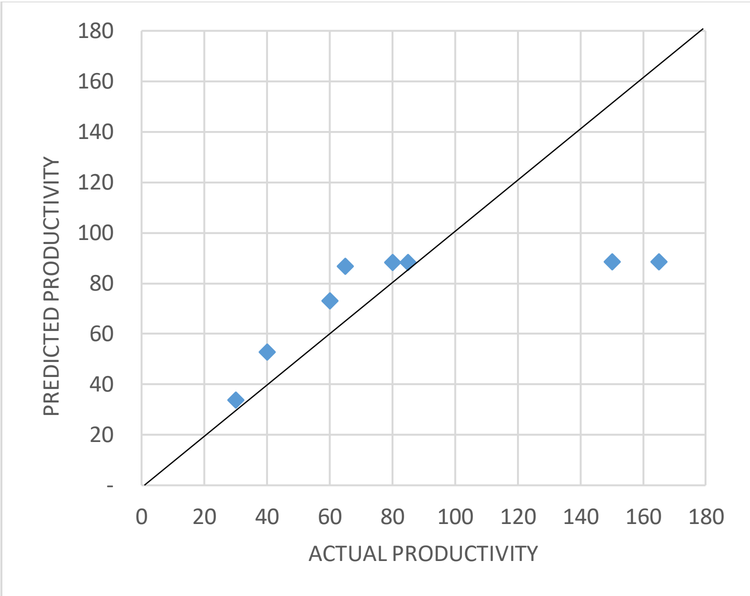

Figure 6. The actual and predicted values of the WRMC dataset **.**

3.3. Indirect factors influencing the productivity

Directly or indirectly, each construction project is influenced by a wide variety of factors. The loss of construction productivity is usually because of a number of factors. Moreover, the factors that affect the construction batch plant productivity is rarely independent of the others; some factors may be the result of the same reason, or one factor may trigger the occurrence of others **(Dai, and Srinivasan, 2009)**. There was a decade of previous efforts to a causal relationship between the factors and productivity by and measuring the factors and measuring the effects on productivity **(Chan and Kaka, 2007)**. Because the ideal conditions considered by manufacturers can rarely allow real construction projects, the actual production can be different from the nominal production.

The results showed that the acceptable values of Cronbach's alpha (α), which is used to check the reliability of data; however, the value of (α) was (91.7%). **(Pallant J. 2013)** assumed the value of (α) more than 70 % is acceptable while (**Bonett D. G. and Wright Th. A., 2014)** assumed the value of more than 90 % is excellent.

As shown in **Table 6.** the Operator's staff skills were the most important factor followed by frequent failure of concrete and lack of construction materials. In contrast, the factor project urbanity was the less effect.

Table 6. Ranking of factors affecting productivity.

No	Factors	Category	Mean	Std. Deviation	RII %
1	OOperator'sstaff skills	Management	4.50	0.65	90
2	Frequent failure of concrete	Site	4.47	0.60	89.4
4	Lack of construction materials	Site	4.45	0.65	89
3	Age of plant	Batch plant	4.42	0.64	88.4
5	Poor safety and Accidents	Management	4.34	0.67	86.8
6	Poor management or supervision	Management	4.32	0.84	86.4
7	Quality control	Management	4.13	1.07	82.6
8	Temperature effects	Site	4.13	0.84	82.6
9	Non-availability of fuel	Batch plant	4.08	0.88	81.6
10	Efficiency of procurement plan and supplying of construction materials.	Management	4.05	0.96	81
11	Impact of rain and other climatic factors	Site	3.97	1.05	79.4
12	Delayed supplying of containers with fine and coarse aggregates	Site	3.95	0.90	79
13	Slow pumping of cement into the silo	Site	3.92	0.97	78.4
14	Truck mixers efficiency	Batch plant	3.89	0.69	77.8
15	The existence of automatic control mixing	Batch plant	3.84	0.75	76.8
16	Specification requirements and construction tests	Site	3.79	1.07	75.8
17	Truck mixers ddrivers'efficiency	Management	3.76	0.75	75.2
18	Number of cement silos	Batch plant	3.76	0.88	75.2
19	Equipment breakdown	Batch plant	3.71	1.01	74.2
20	Cooperation and coordination between staff working	Management	3.63	0.63	72.6
21	Poor Regular progress control	Management	3.61	0.95	72.2
22	Spares not available	Batch plant	3.61	1.03	72.2
23	Working space availability	Site	3.55	0.80	71
24	Machines maintenance efficiency	Batch plant	3.53	0.89	70.6
25	The nature and complexity of the project	Site	3.39	0.89	67.8
26	Incentive payments	Management	3.26	1.08	65.2
27	Misuse of time schedule	Management	3.24	1.05	64.8
28	Size project	Site	2.53	1.11	50.6
29	The project urbanity	Site	2.47	0.95	49.4

6. CONCLUSIONS

After selecting the best model for artificial neural network ANN of productivity for both the dry ready mixed concrete DRMC and the wet ready mixed concrete WRMC successfully, the conclusion can be summarized as below:

- Mostly, the actual productivity of construction equipment in the site did not match the nominal productivity since it comprised lots of uncertainties related to the effected factors.

- The skills of the operators, frequent failure of concrete, and lack of construction materials were the most important factor that affected productivity.
- ANN model showed satisfying results of the validation dataset with a range of the training dataset and poor results with the data that exceeded the range of the training.

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