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Improvement of Productivity in Buildings Construction

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Abstract

Improving productivity in construction projects has long been a major concern, and much research has been carried out to try to ameliorate construction productivity. To this end, this study aims to improve and increase the productivity rate of flat slab formwork used in residential construction projects. A survey consisting of 150 questionnaires was undertaken to identify the factors that influence on the productivity. Based on the relative Importance Index (RII), data on eleven factors deemed to affect productivity were selected. A collection of 100 data points from various sites were utilized to develop two models. Firstly, an Artificial Neural Network (ANN) model was employed, and secondly, a parametric approach was investigated. The data were divided into two sets, with 70% of the data used for training and the remaining 30% used for testing. The models' performance was evaluated using the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values. In the test phase, the artificial neural network model yielded an MSE value of $2.6610e^{-4}$ and a MAPE value of 4.9227, whereas the parametric model produced an MSE of 0.040 and a MAPE of 9.525. It was found that the artificial neural network model provided reliable prediction accuracy compared to the parametric model. However, the artificial neural network approach can be selected as a robust model in predicting and controlling the productivity rate in local construction projects by using the developed model based on the identified factors.

Keywords: Artificial Intelligence, Construction Industry, Artificial Neural Network, Labour Productivity, Parametric Approach

1 Introduction

In the construction industry, productivity can be defined as the quantity of production work per corresponding input [1]. This relationship can take different forms, defining labour productivity when using work-hour as an input or cost productivity when cost input is taken into account [2, 3]; however, this simple definition of factors does not seem realistic and cannot give robust and accurate results, as omitting the influence of other factors can affect productivity. Various research studies have been conducted over many years to estimate, predict and improve the productivity rate in the construction industry, taking into account the effect of different influencing factors.

The review of the literature in the area of construction and specifically productivity improvement can be divided into two main parts, the first focuses on the identification of factors affecting productivity, and the second deals with applications of artificial intelligent.

The pace of labour productivity is a critical factor that directly influences the outcome of projects, ultimately determining their success or failure [4, 5]. According to [6], factors affecting labour productivity may vary from country to country and from site to site, and may also vary within a site. [7] Stated that, labour productivity is influenced by various factors, including external conditions, site conditions, and workers' characteristics. The combined influence of these factors determines the overall level of efficiency and effectiveness attained in construction tasks. [8] Invited 180 Kuwaiti companies to participate in a sample survey that included 45 factors grouped into four groups, to identify the factors most influencing Kuwaiti projects, the result of the statistical analysis determined that the total project cost could be reduced by focusing on the design phase. The influence of several factors on labour productivity in Malaysian construction sector was examined in [9], the authors found that project management skills were the factors that had the greatest impact on productivity, and also stated that the implementation of new technologies in construction sector has positive effects on labour productivity. Another study by [10] highlights that the management group ranks first in three categories, which includes 30 factors studied for their effects on labour productivity in Egyptian construction firms, the authors also found that workers experience and skills were the most important factor. A questionnaire survey conducted in Trinidad and Tobago by [11], to identify the influencing factors on construction projects, were investigated on 30 contractors who are members of the Contractors Association. The survey included 42 factors categorized into four groups: Management, Technological, Human/Labour, and External. Both close-ended and open-ended queries were used, and the respondents were asked to score each factor based on a Likert Scale, ranging from 1 to 4, indicating the effect level. To determine the rank of each factor, the researchers calculated the Relative Importance Index (RII%) and ranked the factors accordingly. The top three influencing factors identified were: the lack of labour supervision, unrealistic scheduling and expectation of labour performance, shortage of experienced labour. In [12], 52 factors, were used to investigate their influence on productivity in Yemen, by calculating the relative importance index, the authors found that workers experience and skills were the most significant factors. [13] Proposed a fuzzy fault tree-based approach to identify factors influencing labour productivity in Lithuania. Initially, they gathered data from 15 experts who evaluated 27 factors using a Likert scale, ranging from 1 to 5, to indicate the degree of severity. After this step, 18 factors with a Relative Importance Index (RII) greater than 0.7 were selected for the subsequent analysis. In the next phase, the authors constructed a fault tree structure through multiple sessions and expert interviews to define the interrelations among the selected factors. Finally, the fuzzy approach was employed to evaluate the contribution of each factor. The results of their analysis indicated that two factors, namely "inflation in the cost of execution" and "improper project financing," were identified as the most influencing factors impacting labour productivity in Lithuania. Another study conducted by [14] aimed to identify the factors affecting labour productivity in the South Africa construction industry based on contractors' perceptions. A questionnaire survey consisting of 41 factors was randomly distributed to 96 contractors. The obtained responses were then analysed using descriptive and inferential statistics. The factors were ranked according to their P-values, and the most significant influencing factors on labour productivity were found to be: excessive bureaucracy, late delivery of materials, industrial action resulting from political activities. Authors in [15] identified factors affecting labour productivity in Australian construction projects by following a three-step approach. In the first step, they conducted a questionnaire to gather data on various factors related to labour productivity in construction projects. The second step involved drawing a cause-and-effect feedback loop to identify the complicated interrelated links between the 38 factors. Lastly, the authors used the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to prioritize the factors. The results of the study revealed that project size, level of skill and experience, and communication problems with foreign workers were the most significant factors affecting labour productivity in Australian multi-storey building construction projects. In another research conducted by [16], authors examined the influence of weather conditions on labour productivity in the United Kingdom. The study involved collecting data over a span of 5 years, from September 2017 to August 2022. To gather information, the researchers administered 28 online questionnaire surveys to relevant participants. Based on their findings, the authors proposed implementing modular techniques in construction, wherein certain elements are produced in factory settings with controlled environments. This approach is expected to mitigate the adverse effects of weather on construction projects, consequently reducing overall costs.

In the second half of the 1980s, Artificial Neural Networks were developed and used to solve various construction problems such as cost estimation, duration and productivity. Numerous models were produced [17–19],and are still in progress to this day. [20] Examined the influence of ten factors, on Turkish formworkers' productivity. A three-layer feed-forward back propagation neural network was used, using these factors as input variables, a hidden layer containing five hidden neurons and an output neuron to estimate the labourers' productivity rate, compared to the estimate of the Turkish Ministry of Public Works and Settlement, the simulation results indicate that the model developed accurately predicted the total man-hours required. In another approach, [21], also formulated a multi-layer ANN with the backpropagation algorithm using ten influencing factors, as input variables to assess the labour productivity rate for finishing work on marble floors. The architecture of the model used was a three-layer neural network with one hidden node in the hidden layer and used the hyperbolic tangent sigmoid function as a transfer function, a degree of accuracy of 90.9% was recorded, which proved that Network, the Backpropagation Neural Network, the Radial Base Function Neural Network and the Adaptive Neuro-Fuzzy Inference System, and compared their results to choose the best model the developed model can reliably predict the productivity rate, it was also found that the most influential factors on productivity were age, number of workers and experience. Two ANNs models with different architectures were developed by [22], using three categories of influencing factors, the capabilities of a Feed-Forward neural network and a Radial-Based NN to predict masonry crew productivity were compared; the results showed that the RBNN technique predicted productivity better than the FFNN. Authors in [23] took thirteen factors that were found to have a negative effect on labour productivity and considered them as inputs for developing an ANN model to estimate bricklayer productivity, a gradient descent momentum backpropagation was used as a training algorithm for the model which has three hidden layers and a hyperbolic tangent sigmoid transfer function; accurate results were obtained using this architecture, in addition, the results of the sensitivity analyses led to the conclusion that the wall thickness was the factor that most influenced the labour productivity rate. [24] Developed four ANN models based on different techniques, including the General Regression Neural for predicting the productivity rate of formwork labours, the performance results show that the Backpropagation NN is the best model among the four techniques developed in the study.Authors in[25]stated that labour productivity in Saudi construction projects is affected by a number of factors and can be quantified using mathematical models. For this purpose, the author developed four different models based on multilayer perceptron neural network

(MLPNN), general regression neural network (GRNN), support vector machine (SVM), and multiple additive regression trees (MART) to assess the productivity rate of concrete construction activities and compared the results of the developed models. The GRNN model was found to be the best estimator model for labour productivity of steel fixing and concrete pouring, while the MART model provided better results than the others for formwork assembly productivity. In order to ensure effective and efficient project delivery,[26] utilized an artificial neural network (ANN) to assess the relationships between various factors and bricklaying productivity during the pre-planning phase. The developed model included 7 input factors, 5 hidden neurons, and one output. The results showed good performance, indicating that the ANN model can be utilized to enhance project delivery by providing a more realistic estimation of productivity rates. This, in turn, leads to better planning, cost estimation, and resource allocation. In a study conducted by [27], authors used sets of five Artificial Neural Network models to develop a single model capable of estimating steel reinforcement works. They collected 145 data points from construction sites in Poland, which were then divided into 90% for training and 10% for testing purposes. The proposed model demonstrated satisfactory performance, indicating its robustness in estimating steel reinforcement works. [28] Developed an Artificial Neural Network (ANN) model to assess the productivity rate of piping assembly activities in Brazilian projects. They tested 108 different Feedforward Neural Network (FFNN) architectures, each with 14 input neurons, to select the best model. The research results indicated that the Mean Square Error (MSE) of the chosen model reached the value of 9.67E-04, demonstrating satisfactory performance and accuracy. A hybrid model combining artificial neural network (ANN) and Grasshopper Optimisation Algorithm (GOA) was developed by[29]. The objective was to identify the factors with the greatest impact on labour productivity in Iranian construction projects and improve the accuracy of labour productivity prediction. Out of the 19 factors initially considered, only 6 factors were identified as influential and utilized to develop the predictive ANN model. [30] Employed Artificial Neural Networks (ANN) to predict the productivity rate for brick masonry work. The authors conducted a questionnaire survey that initially included forty-four factors. However, based on the Relative Importance Index (RII) analysis, only the top 13 ranking factors were considered as inputs for the model. The developed model utilized a three-layer backpropagation-feedforward neural network with one hidden layer consisting of 30 hidden neurons. The Mean Squared Error (MSE) was used as a measure of accuracy for the model. The results indicated that the developed model effectively estimated brick masonry productivity by considering the impact of the selected 13 factors.
Parametric model was developed in the early 1960s, it has been used to find the relationship between the response and one or more factors, usually by applying regression analysis to the parameters [31]. [32] Developed a parametric equation based on multiple linear regression (MLR) analysis to model the labour productivity of marble floor finishing works in Iraq.100 data including 10 influencing factors were collected and used to predict productivity, good performance, and a high correlation was obtained, indicating a good relationship between the response and the factors, and the model can be reliably used to estimate productivity. In another study conducted by [33] to estimate the percentage loss or increase in construction labour productivity, 14 influencing factors were defined and used to develop a regression model, the author argued that the proposed model can accurately predict construction labour productivity. [34] Examined the influence of various buildability factors on the labour productivity of structural elements, by developing a MLR model to assess the relationship between design characteristics and labour productivity. The results show that the model can provide information

for designers to adapt their designs to achieve the best labour productivity performance.Authors in [35] conducted a study to examine the impact of worker experience and skill level on masonry construction productivity in Vietnam. They developed a logistic regression model to estimate productivity and found that there was no difference in average productivity between different worker experience groups. However, they did observe a significant difference in productivity between worker skill groups. [36] Employed a multiple linear regression method to analyse the impact of three factors on labour productivity in lightweight brick wall installation and lightweight brick wall plastering in Indonesia. The researchers achieved an impressive accuracy of 99.43% and 99.04% for the two respective models, indicating the robustness and reliability of the developed models. In their study conducted at eight construction sites in Niš, Serbia, [37] Focused on analysing concreting processes, particularly those related to columns and walls. They gathered 60 data points to develop regression analysis and Simulation models aimed at improving the accuracy of forecasting productivity rates for concrete works. The findings of the study indicated that these proposed models have the potential to enhance decision-making and improve the accuracy of planning in construction projects involving residential buildings in Niš, Serbia.

The Algerian construction industry is currently facing a major problem in accurately measuring construction labor productivity. This issue is mainly attributed to the continued utilisation of traditional technologies, which has significantly hindered progress in the construction sector. The challenges are particularly evident in the execution of flat slab formwork activities, resulting in excessive resource consumption in terms of manpower, time, and cost. To enhance construction efficiency, time management, and cost control, it is crucial to address the productivity issues related to flat slab formwork. By optimizing the flat slab formwork productivity in Algerian building projects, it becomes possible to achieve faster construction cycles, lower labor costs, and improve overall project performance. This, in turn, leads to more efficient resource utilization and successful project outcomes.

While previous studies have examined construction productivity in a general context, however, there appears to be a noticeable gap in the existing research regarding comprehensive investigations into the factors influencing productivity, particularly in Algerian construction projects. Additionally, there is a lack of intelligent methods that specifically concentrate on accurately measuring and estimating labor productivity rates for flat slab formwork within the context of the local construction industry. Since our study focuses on a local problem with specific characteristics compared to other world regions, we are faced with the following issues:

- What are the key factors that influence productivity in Algerian construction projects?
- How do the identified factors influence the productivity rate of flat slab formwork in Algerian construction projects?
- How can we estimate this productivity?

This paper aims to address two primary objectives: identifying the key factors that affect productivity in Algerian construction projects and developing intelligent models capable of estimating the labour productivity rate of flat slab formwork. By conducting research on this topic, the study intends to fill the existing knowledge gap and contribute valuable insights to both academia and industry practitioners. The findings of this research will provide valuable guidance for productivity improvement and decision-making in the management of construction projects in Algeria.

2 Methodology

This study aims to improve the labour productivity rate of flat slab formwork in Algerian building projects. To achieve the objective mentioned, the methodology presented in this section was adopted.

2.1 Questionnaire Survey Analysis

Identifying factors that negatively affect labour productivity in construction projects has been a major concern for managers [32, 38]. After careful analysis of the top influential factors cited by researchers [10, 12], [21-23], [39–43], the factors that appeared repeatedly were identified and extracted. Moreover, by considering on-site observations of construction projects, a questionnaire survey was designed including 16influencing factors classified into three main groups as shown in Table 1.The survey consisted of closed-ended questions that were sent by email to local expert, who were asked to rate the impact of each factor on labour productivity using a five-point Likert scale, ranging from 1 (indicating the least impact) to 5 (indicating the greatest impact). Respondents were specifically asked to indicate the extent to which a specific factor affected labour productivity according to their own perception. The designed questionnaire survey was divided into three sections:

1. The first shows the respondents' personal information (position and professional experience)
2. The second section consists of three groups with 16 influencing factors, the respondents rank the importance of each of them based on a five-point Likert scale, where 1 indicates the least impact while 5 represents the greatest impact.
3. The last section represents a space dedicated to the respondents' opinions.

Table 1: Questionnaire survey factors

Questions (Factors)		
Group 01: Management	**Group 02: Factors related to workers**	**Group 03: External factors**
Small crew size Low wages Formwork condition Delay in payment of the company by the project owner Congestion in the workspace Poor control Low workers motivation	Work-hour/absenteeism Worker's experience Quantity of installed work Worker's age	Weather condition Humidity High temperature Low temperature Shortage of building materials

2.1.1 Sample Size

For a more diverse and precise analysis, we specifically targeted project managers, technical managers, site managers, civil engineers, and architects working in the public and private sectors to gather their perceptions and viewpoints on the various factors that influence labour productivity in the Algerian construction industry. A statically representative sample of the population was obtained using a formulae developed by [12, 44], as expressed bellow:

$$n = \frac{m}{1 + \frac{(m-1)}{N}} \tag{1}$$

where, *n* is the sample size of the limited population, m is the sample size of the unlimited population, and *N* is the sample size of the available population. *m* is estimated as follows:

$$m = \frac{z^2 \times p(1-p)}{\varepsilon^2} \tag{2}$$

z represents the statistic value for the confidence level used (*z* = 1.645 for 90% confidence level), *ε* is the sampling error of the point estimate, and *p* is the value of the population proportion that is being estimated, for which [45], proposed using a conservative value of *p* = 0.50 to obtain a sample size at least as large as needed. The value of *m* can be obtained than:

$$m = \frac{(1.645)^2 \times 0.50(1-0.50)}{0.1^2} = 67.65 \simeq 68 \tag{3}$$

In this study, a total number of 150 available samples were selected, based on this; the required representative sample size of the population is obtained as follows:

$$n = \frac{68}{1 + \frac{(68-1)}{150}} \simeq 47 \tag{4}$$

A total of 150 samples were distributed by email and only 56 feedbacks were received, this number of completed questionnaires met and exceeded the required sample size. The respondents in the samples are project managers, technical managers, site managers, civil engineers, and architects, working in Algerian construction industry. 48.22% of them having an experience of 1 to 4 years, while 44.64% have an experience of 05 to 09 years, and the remaining 7.14% have 10 or more years of experience.

2.1.2 Defining the Influencing Factors

The Relative Importance Index (RII) technique was used to define the most influential factors; this index was calculated according to equation (6).

$$RII(\%) = \left(\frac{\sum_{i=1}^{5} n_i \times x_i}{5\sum_{i=1}^{5} x_i}\right) \times 100 \tag{6}$$

where, n_i indicates the Likert scale from 1 to 5, and x_i denotes the frequency of each n_i.
The results of the RII show that three factors had an RII greater than 80%, whereas nine factors have an RII between 70 and 80%, while the RII of the other four factors is in the range of 60% and 70%. Table 2 summarizes the results of RII and the rank of each factor.

Table 2: RII (%) Results and rank of each factor

Factors	RII (%)	Rank
Small crew size	78.21	07
Low wages	89.64	01
Formwork condition	84.29	03
Congestion in the workspace.	71.79	12

Poor control	74.64	09
Delay in payment of the company by the project owner	74.29	10
Low workers motivation	86.07	02
Work-hour /absenteeism	78.93	04
Worker's experience	78.57	05
Quantity of installed work	78.57	05
Worker's age	68.57	13
Weather condition	68.57	13
Humidity	65.00	16
High temperature	75.36	08
Low temperature	67.14	15
Shortage of building materials	73.93	11

In this study, factors with an RII (%) greater than 75% were taken into account. On this basis, the most relevant factors deemed to affect the productivity rate are: workers' wages, workers' motivation, formwork condition, number of working hours, workers' experience, crew size, quantity of installed work, and temperature. Table 3 summarises all the factors considered.

Table 3: The selected influential factors

Factors	Categories	Classification
Number of working hours	Quantitative	Numerical
Number of formworkers	Quantitative	Numerical
Number of unskilled workers	Quantitative	Numerical
Minimum workers' experience	Quantitative	Numerical
Maximum workers' experience	Quantitative	Numerical
Formwork condition	Qualitative	Mediocre Average Good
Type of workers' motivation	Qualitative	Extra money Recuperation days Piecework
Temperature	Quantitative	Numerical
Wage of formworkers	Quantitative	Numerical
Wage of unskilled workers	Quantitative	Numerical
Surface area of the slab formed	Quantitative	Numerical

2.2 Data Collection

The data for this study were collected daily, based on in site observations on the flat slab formwork task, a number of 100 data samples, comprising 11 quantitative and qualitative influencing factors, were compiled from construction projects in different regions of Algeria, the qualitative factors used in this study were transformed into numerical values for use in the models (Table 4). As indicated in the previous sections, productivity can be calculated in different ways (total or partial factor productivity) [46], the type of labour productivity, which is of interest in this study, is defined as the ratio of output to worker-hour (Equation 7), noting that the output presents the surface area of the slab that was carried out in square metres.

$$productivity\ rate = \frac{output}{man \times work\ hour} \tag{7}$$

Table: 4 Transformation of qualitative factors into numerical form

Qualitative factors		**Numerical transformation**
Formwork state	Mediocre	-0.50
	Average	0.00
	Good	0.50
Type of motivation	Extra money	0.10
	Recuperation days	0.15
	Piecework	0.20

2.3 Artificial Neural Network Model Development

2.3.1 Data Preprocessing

The preprocessing phase consists of preparing the data before introducing them into the model, which gives the network the capacity to converge more quickly and to better generalise the results obtained. In this phase the input and target data were normalised to be within the range of [0 to 1] both for the training and the test phase using equation (8).

$$X_n = \frac{X_i - X_{i_{min}}}{Xi_{{min}_{i_{max}}}} \quad (8)$$

where: X_n: the value of the variable (x_i) after normalization. And X_i: the value of the variable before normalization. X_i min; X_i max are the minimum and maximum value of (X_i).

2.3.2 Data Processing

Is the process by which the collected data is organised and introduces into the ANN model, to obtain better generalisation of the results, for this purpose, the designed set was divided into training and test subsets, the training subset is used to initialise the weights and biases of the network. According to [47], each network starts training from arbitrary initial weights and biases, while the test subset is used to verify the network design, testing the efficiency of the model on the new data. During the modelling phase, a phenomenon can occur when errors begin to increase in front of the test data after providing very small values in the training sets, this phenomenon is known as over fitting, in this case, the model adjusted its parameters well and stored all the training courses, but when new data was introduced into the network, the model failed to adapt and generalise the new situation. Different methods have been used to avoid this phenomenon; in this study the Bayesıan regularisation technique was used.
Simulation software was utilized to create, train and test the networks, with random division of the designed set into 70% training, and 30% into test sets.

2.3.3 Model Architecture and Adapted Algorithm

The model architecture represents the number of appropriate layers, and the way these layers are connected, as well as the type of algorithm chosen. In this study, several architectures were tested to obtain better accuracy, the model with three layers having 11 input neurons, two hidden layers having 15 and 10 hidden neurons in the first and second hidden layers respectively, and one output neuron as presented in Figure 1. Backpropagation was used as a learning algorithm with Bayesian regulation.

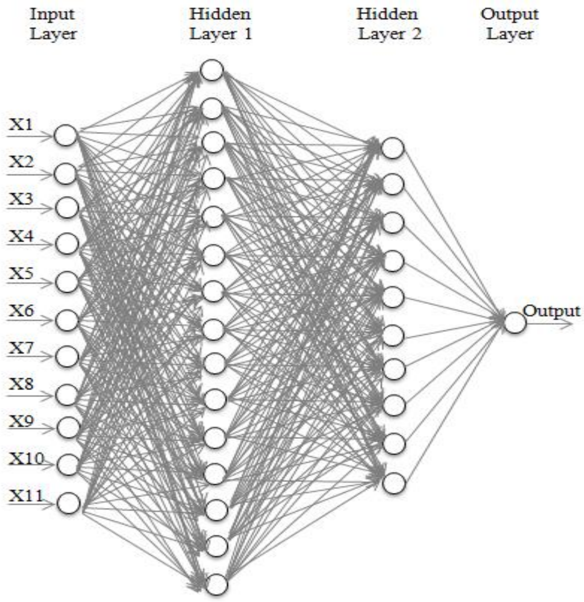

Figure 1: The architecture of the ANN model developed

2.3.1 Transfer Function

The transfer function is a monotonic, continuous, increasing and differentiable function applied to the sum of the weighted inputs of the model to produce their resulting outputs. This function consists of two sub-functions used by the neurons in the different layers. Firstly, the neuron in each layer receives a linear combination of weighted inputs, determining the sum of the information collected, using the activation function A(x) which is given as follows:

$$A_i(x) = \sum_{j=1}^{N} \left(W_{ij} \times X_j\right) - \theta_i \tag{9}$$

where: X_j: the inputs, and W_{ij}: the weights and θ_i is the threshold (bias).
In the next step, the neurons use an O(A) output function, to keep the output values within a specified range, operating it on the activation function which has a scalar format and returns the scalar output neurons. Thus, the transfer function O(A(x)) is the combination of the two previous functions (activation and output function), which is used to produce the final output neurons [48]. Different transfer functions are available in the Artificial Neural Network model used to pass information from one layer to the other [47], the most commonly used are log-sigmoid, tan-sigmoid, and linear (purelin). Each function of the latter has its own range that generates output results within it. The logsig produces results between 0 and 1 while tansig returns outputs in the range of -1 and 1, however, the specific range of purelin is: [-∞ + ∞].
The transfer functions adopted in this study for the implementation of the ANN model were the log-sigmoid transfer function (logsig) and the hyperbolic tangent sigmoid (tansig) which were used in the first and second hidden layers, respectively, while the pureline linear transfer function was used in the output layer equation (10), equation (11) and equation (12).

$$Log\,sig(A) = \frac{1}{(1 + exp(-A))} \tag{10}$$

$$Tansig(A) = \frac{2}{(1 + exp(-2A))} - 1 \tag{11}$$

$$F(A) = A \tag{12}$$

2.3.2 Training and Testing Phase

Network training is the first process carried out by the model to select its parameters, it consists of adjusting the values of weights and biases until a minimum error value is reached and the best performance is obtained. The Bayesıan regularization training algorithm was used in this study to obtain better results. This algorithm consists of adding an additional term (penalty term), which represents the sum of the squares weights to the equation error, and then propagating the resulting errors back to readjust the weights and biases, and minimizing the errors to obtain the best prediction of the output.

Out of the 100 datasets collected, a number of 70 datasets were used for training in the first phase, while the remaining 30 datasets were retained to test the model in order to generalize the model to the new data, and to obtain better performance in predicting the results.

The Mean Square Error (MSE) and the Mean Absolute Percentage Error (MAPE) were used in this study to calculate the performance of the model, as follows:

$$MSE = \frac{\sum_{i=1}^{n}(x_i - E_i)^2}{n} \tag{13}$$

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \left|\frac{x_i - E_i}{x_i}\right| \tag{14}$$

where, *n* is the number of the data, *E* is the model outputs, and x_i is the actual value.

2.4 Parametric Analysis

Parametric analysis is a method that links a variable to be estimated (labour productivity) and the different factors that influence it through a mathematical relationship. The technique most commonly used to develop the parametric equation is Multiple Linear Regression (MLR).

2.4.1 Development of Multiple Linear Regression Model

At this stage, 70% of the total data collected, were used to develop the model using Statistical Product and Solutions Services (SPSS) software. The correlation test was carried out to check the relationship between the response and the explanatory variables. The results of the correlation coefficient (R) and determination coefficient (R2) presented in Table 5 show a strong correlation between the response (flat slab formwork productivity rate) and the explanatory variables, indicating that they have a good relationship. A significant value for the model was found to be less than 0.05, meaning that the regression line fits the data well.

Table 5: Model Results Summary

Coefficient of correlation (R)	**Coefficient of determination (R2)**	**Significance of the model**
0.958	0.917	0.000

Table 6 summarises the results of MLR coefficients and the resulting equation for estimating the productivity rate of flat slab formwork in construction projects takes the form below:

$$\begin{aligned} Y = 3,239 - 0,304X_1 - 0,088X_2 - 0,139X_3 - 0,021X_4 \\ +0,007X_5 - 0,015X_6 - 1,356X_7 + 0,011X_8 \\ -0,004X_9 + 0,000103\, X_{10} - 0,000053X_{11} \end{aligned} \tag{15}$$

Table 6: Coefficients of Multiple Linear Regression

Model	**Unstandardized Coefficients**	
	ß	**Std. Error**
(Constant)	3.239	0.716
X1	-0.304	0.024
X2	-0.088	0.035
X3	-0.139	0.014
X4	-0.021	0.024
X5	0.007	0.010
X6	-0.015	0.047
X7	-1.356	1.302
X8	0.011	0.001
X9	-0.004	0.006
X10	0.000103	0.000046
X11	-0.000053	0.000039

2.4.2 Validation of the Developed Model

Model validation is the stage during which the new data was used on the explanatory variables (factors) to test the ability of the parametric equation developed in equation (15), to estimate and predict the productivity rate of the flat slab formwork. In this respect, a set of 30 data was applied to the developed parametric equation, and the results of the predicted productivity rate were compared with the actual productivity rate. The MSE and MAPE measures were calculated to verify the performance of the model with the new data.

3 Results and Discussion

This paper aims to develop a machine learning model capable of predicting and estimating the labour productivity rate for flat slab formwork assembly. In this respect, an Artificial Neural Network was first trained using 70% of the data sets and tested using 30% of the data sets. Various ANN architectures were tested with different combinations in the number of hidden layers and hidden neurons as well as in the learning algorithm, and in the different ANN parameters, to choose the best model that gives the best performance, the final structure adopted in this study was a three-layer feed-forward back-propagation neural network having two hidden layers with 15 hidden neurons and 10 hidden neurons in the first and second hidden layers respectively. The Bayesian regularization technique was adopted as the learning algorithm. The modelling phase consists of training the network first; in this step, the model shows its ability to predict the results of the labour productivity rate with lower values of the MSE and the MAPE, as shown in Figure 2. Testing the network is the next step carried out by the model to examine its ability to handle unseen data. Good results from MSE and MAPE were obtained at this stage as well, showing the model's ability to predict the labour productivity rates of flat slab formwork, as shown in Figure 3. In line with the results from the MSE and MAPE, it can be said that the model developed performs well and that no significant difference could be observed between the predicted and actual labour productivity rates. Table 7 summarises the overall results of the measures. The regression analysis in the developed ANN model was carried out to examine the relationship between actual targets and estimated output, a correlation coefficient of 0.9994 was obtained indicating a good linear correlation between forecasted and actual labour productivity (Figure 4).

In the second part of the study, a parametric analysis of the collected data was carried out by developing a Multiple Linear Regression model. The results of the correlation coefficient and the determination coefficient rather than the significant value of the developed equation show a strong correlation between the response (labour productivity rate) and the explanatory variables (factors). A good result from MSE and MAPE was obtained, indicating that the parametric equation developed has the capacity to estimate and predict the labour productivity rates of flat slab formwork (Figure 2). A set of 30 data was applied to the developed parametric equation to validate it and the results of the predicted labour productivity rates were compared to the actual labour productivity rates. Based on the MSE and MAPE results obtained during the validation phase, it can be stated that the parametric equation developed works well and can be used reliably to predict the labour productivity rates of flat slab formwork (Figure 3). Table 8 lists the results of the performance of the parametric model.

Finally, from the results of the two methods above, it can be seen that both the ANN model and the parametric model can be reliably used to estimate and predict the labour productivity rate. However, significant differences between the performances of the two models developed were observed, so we can conclude that the ANN model gives better results and predicts the labour productivity rates of flat slab formwork better than the parametric model.

Table 7: Results of the Artificial Neural Network performance

Phase \ **Performance**	**MSE**	**MAPE %**
Training phase	8.0796e-05	0.82832
Test phase	2.6610e-04	4.9227

Table 8: Results of the parametric equation performance

Phase \ **Performance**	**MSE**	**MAPE %**
Development phase	0.048	9.395
Validation phase	0.040	9.525

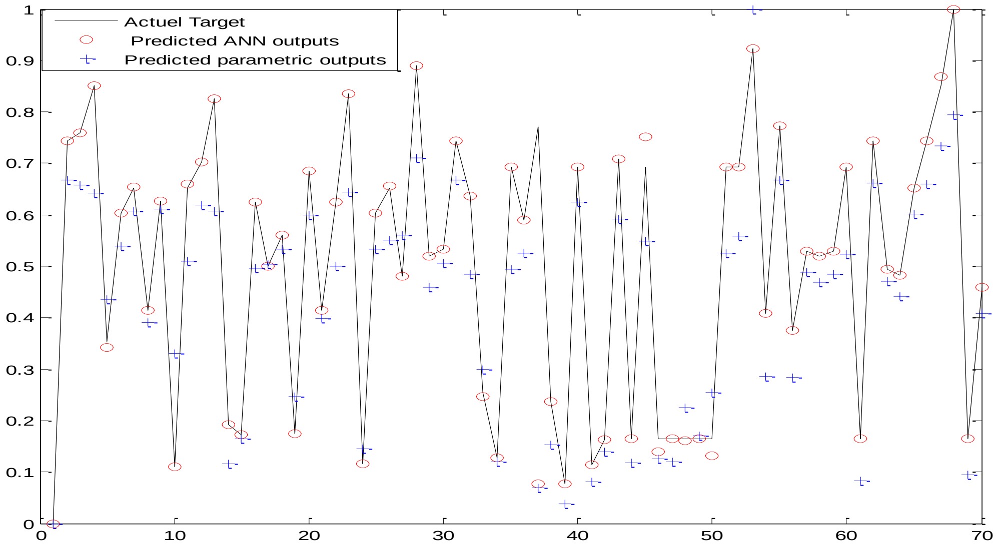

Figure 2: Predicted Neural Network and parametric outputs versus actual targets in the training phase

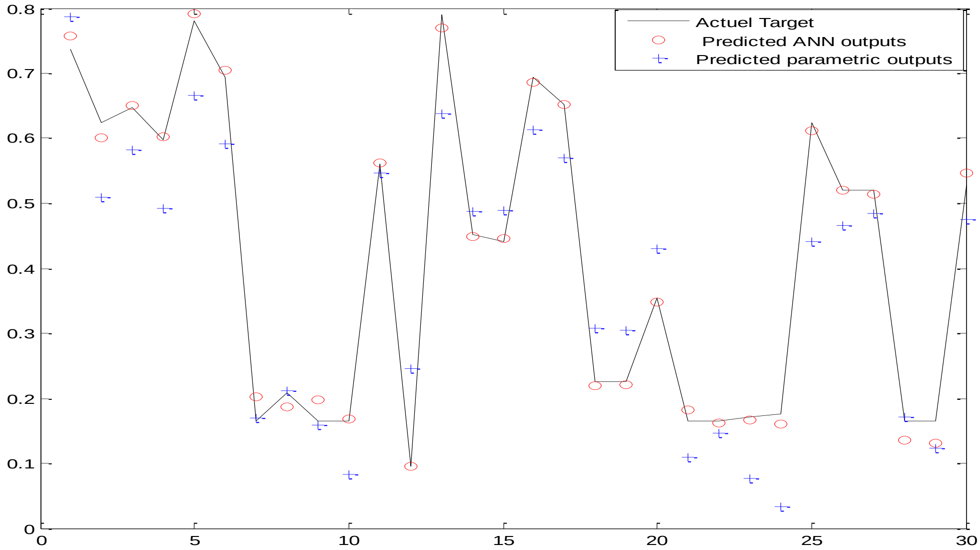

Figure 3: Predicted Neural Network and parametric outputs versus actual targets in the test phase

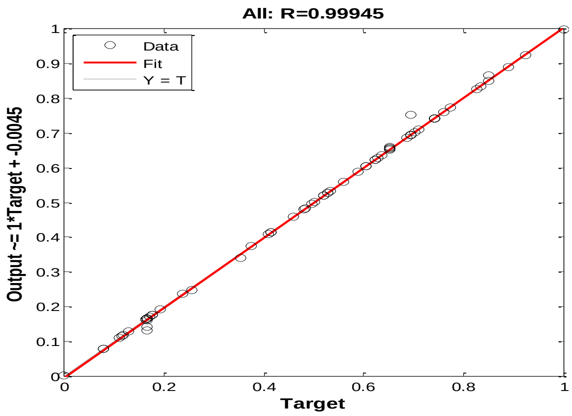

Figure 4: The regression analysis and correlation coefficient R in ANN model

Additionally, we investigated samples of previous studies conducted by many researchers on formwork productivity modelling. Results were reported regarding the performance of each model. For instance, [49] obtained a MAPE of 14.55% and 17.69% for the ANN and MLR models, respectively, for column formwork productivity. In another study by [25], the MART model was found to be the best among the four developed models, with an MSE of 0.0937. Furthermore, [24] developed four models for slabs, walls, and columns formwork productivity, it was found that Backpropagation Neural Network was the best model which achieved an MSE of 0.018.
Table 9 describes a comparison study conducted on existing models versus the developed models.

Table 9: Results comparison among existing models

Existing Research	**The used model**	**Performances results in the test phase**
Developed research study	Artificial Neural Network	MSE = 2.6610e-04 MAPE = 4.9227 %
	Multiple Linear Regression	MSE = 0.040 MAPE = 9.525 %
S. Nassar and A. Khaleel. (2019)	Artificial Neural Network	MAPE = 14.55 %
	Multiple Linear Regression	MAPE = 17.69 %
E. A. Mlybari. (2020)	MART	MSE = 0.0937
Golnaraghi et al. (2019)	Backpropagation Artificial Neural Network	MSE = 0.018

By comparing the outcomes of the mentioned models with models developed in this study, it can be observed that the latter exhibits significantly higher performance accuracy. The achieved MSE and MAPE values suggest that our ANN and MLR models are better in predicting formwork productivity and providing more accurate results. This confirms the reliability and efficiency of the methods used in this study, which leading to a significant advancement in the field of formwork productivity modelling.

4 Conclusion

This study presented a development of a multilayer Artificial Neural Network and a parametric equation based on MLR models aimed at predicting and increasing the labour productivity rate of the flat slab formwork in Algerian construction projects. A survey of 150 questionnaires was distributed to define the most influential factors. The total number of data collected on the 11 influencing factors defined in this study was 100, which were then randomly divided into two main subsets. An Artificial Neural Network model was first developed using 70% of the data set, to train the network to update weights and biases, and the remaining 30% was used to test

the network for better generalisation on the new data. The model architecture used was a three-layer feed-forward ANN with a backpropagation algorithm and Bayesian regularisation as a learning function. A parametric equation was developed in the second part of this study, also using the same 70% of the dataset to establish a mathematical equation based on the multiple linear regression method. The remaining 30% of the dataset was used to validate the equation against the new data.
The results of this study clearly show that the ANN model developed is more efficient and gives more accurate prediction results than the parametric equation. However, it can be noticed that both developed models have a good relationship between the predicted results and the actual targets. Moreover, a high performance was recorded, indicating that both models behave well with the unseen data and produce results reasonably close to the actual targets. The results of this research study allow concluding that the ANN model and the parametric equation developed can be reliably used to predict the measurement of the productivity rate with the incorporation of influencing factors deemed to affect the labour productivity of the flat slab formwork task.

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