Assessment the Effect of Labor Motivation on Construction Productivity

Suad Hosny[1], Nourhan Abdel-Aziz[2], and H.E. Hossny[3]

Corresponding author: Suad Hosny

Address: [1]Assistant Professor of Construction Engineering and Management, Department of construction Engineering Utilities, Faculty of Engineering, Zagazig University, Egypt, Tel: 00201001501722, [2]Department of Construction and Building Engineering, Zagazig Higher Institute of Engineering and Technology, Zagazig, Egypt, Tel: 00201024292756, [3]Professor, Construction Engineering and Utilities Department, Faculty of Engineering, Zagazig University, Egypt, Tel: 00201222354331

E-mail: suad_hosny@zu.edu.eg, nourhanabdelazize@yahoo.com, hosny_hosm64@yahoo.com

Abstract

labor productivity is an issue of particular importance to the performance of construction projects. Construction labor productivity is affected by numerous factors these factors include motivation. some researches studied the impact of motivation on labor productivity, but most of these studies relied on expert opinions and perceptions rather than empirical data collected from construction sites. The purpose of this study is to investigate the relationship between labor motivation and their productivity. For this purpose, 14 motivational factors that significantly affect labor productivity were identified from literature, and by using a questionnaire survey, they were shortened to 5 critical factors. a productivity model was developed based on artificial neural network (ANN) and multiple linear regression (MLR) to identify the effect of motivation factors on labor productivity. Data related to labor productivity of brickwork and ceramic work crafts in Egyptian construction projects were collected. The results revealed that ANN technique has better prediction performance than MLR. In order to identify the effect of the motivation factors on labor productivity a sensitivity analysis was conducted. This study adds to the body of knowledge in construction project management by evaluating the influence of labor motivation on productivity. The results can facilitate the prediction of labor productivity, which helps with project cost and schedule management.

Keywords: Effect, labor, construction, productivity.

DOI Number:10.14704/nq.2022.20.8.NQ44419 **NeuroQuantology 2022; 20(8): 3888-3903**

1. Introduction

The construction industry is a very important and effective sector in the national economy (El-Gohary et al., 2017). productivity is regarded as one of the most essential key indicators of construction project performance (Shiru et al., 2020). Construction productivity has been identified as a major factor influencing project schedule and its budget. Low productivity leads to time and cost overruns (Momade and Hainin, 2018). Construction productivity is heavily influenced by labor. Labor costs account for a significant component of construction projects' budgets, accounting for approximately 30-60% of total project costs (Gomar et al., 2002; El-Gohary et al., 2017).

Construction productivity is affected by numerous factors these factors include low motivation, payment delay, poor supervision, inadequate communication, interesting work, training and development, rework, change orders, shortage of material and other different factors (Momade and Hainin, 2019). Several studies indicated the effect of motivation on the productivity and illustrated that motivation is one of the most important factors affecting construction labor productivity (Jarkas and Bitar, 2012). Motivation guides an individual's behavior toward a goal and boosts commitment to work, resulting in increased productivity (Sivaraj and Vidivelli, 2018). But, much of the evidence has been discovered to be anecdotal or reliant on expert opinion (Li et al., 2019). This puts the industry and the scientific community in a quandary in recognizing the factual role of motivation in increasing construction labor productivity (Du et al., 2020). The purpose of this study is to discover if there is an actual empirical relation between labor motivation and their productivity. For this purpose, an exhaustive literature review of motivation and productivity was conducted. The artificial neural network (ANN) and multiple linear regression analysis were then used to create a model to quantify motivation and predict labor productivity. Actual productivity was measured and compared to predicted productivity to estimate the modelling productivity's percentage accuracy. The findings assist construction companies in devising measures to boost labor productivity among construction workers.

2. Literature Review

2.1 Labor productivity in construction

Productivity is defined as the relationship between the output of a production and the input used to produce that output. As a result, productivity is described as the effective use of resources such as labor, capital, energy, and information in the production of various services. The term of productivity can be defined in a variety of ways (Prokopenko, 1987). According to Jarkas (2005) productivity is "The relationship between production and the resources by which that output is produced". Productivity is defined as "the amount of work achieved per man-hour, machine-hour, or crew-hour" (Finke, 1998). Arditi and Mochtar (2000) defined productivity as "the ratio of total outputs to total inputs in dollars,". According to previous definitions productivity in construction industry is defined as the ratio of output to input, as shown by Eq. (1)

Productivity = $\frac{output}{input}$ (Heizer and Render, 1999) (1)

productivity has two measures: (1) total productivity, which is the ratio of total output to total inputs, and (2) partial productivity, which is the ratio of total output to partial input (TaIhouni, 1990). Total productivity takes into account all resources such as labor, equipment, materials, and capital used to produce output as expressed in Eq. (2).

Total productivity= $\frac{total\ output}{total\ inputs(labor+material+equipment+captial)}$ (2)

Partial productivity measures the relationship of output to one input of labors, material, equipment, or capital. The productivity of labor is considered to be partial productivity (Yi and Chan, 2013). Thomes et al. (1990) described labor productivity in more than one way, as shown below.

Labor productivity = $\frac{output}{labor\ hours}$ (3)

Labor productivity = $\frac{output}{labor\ cost}$ (4)

Several researches have studied the construction labor productivity in different countries. Based on previous researches, various factors which have a sufficient effect on labor productivity were determined, as shown in Table 1.

Table 1. Factors related to construction labor productivity gathered form literature.

Author	Country	Factors
Jaraks et al. (2012)	Kuwait	Clarity of specification; change orders; coordination between design teams; supervision; percentage of subcontracted work; complexity of design; **motivation**; leadership of construction managers; engineer's inspection; and unavailability of information.
Thomas and Sudakumar (2013)	India	Equipment and tools availability; **motivation**; supervision; material availability; site management; suitable drawing management; inadequate project management; lack of communication.
El-Gohary (2014)	Egypt	Labor's skills and experience; **motivation**; material availability; construction management leadership; proper labor supervision.
Heravi and Eslomdoost (2015)	Iran	**Labor motivation;** competence of labor**;** supervision; Technical efficiency; proper planning.

Continue. Table 1. Factors related to construction labor productivity gathered form literature.

Author	Country	Factors
Hiyassat et al. (2016)	Jordan	Planning; relationship between management and workers; experience; availability of equipment; **motivation**; safety; status of workers; effect of religion.
Shiru et al. 2020	India	**Motivation**; manpower; material; safety; management.
Goodarzizad et al. (2021)	Iran	Labor's skills and experience; **labor motivation**; payment; site accidents; competency of supervision; conditions of weather.

2.2 Motivation strategy to improve productivity

Employee motivation has been and will continue to be the decisive factor in work performance that leads to an organization's success or failure, therefore understanding, and implementing it has been a major concern for organizations, managers, and even supervisors (Dongho, 2006). Several studies indicated the effect of motivation on the productivity in the past and at the present time. In the past, Khan (1993) explored how different motivation theories can be used to promote individual productivity in the workplace. The influence of motivation on worker productivity has been proven. The study stated that fairness of payment, monetary incentives, and training were the prime motivators that helped the management to improve productivity.

More recent researches have explained the impact of motivation on productivity in construction domain. Appropriate labor motivation has been proposed as a major factor in increasing worker productivity. It is necessary to recognize those factors that have an influence on motivating the construction workforce in order to properly manage human resources and ensure that the workforce is productive enough (Khan et al.2011). Incentive programmes, which include financial incentives, and non-financial incentives, are one of the strategies for motivating and gratifying workers, resulting in increased productivity (EL-Gohary and Aziz, 2014). Johari and Jha (2020) implemented a research to study the impact of motivation on construction labor productivity. Six motivation factors were measured in India at construction sites, and data was collected from workers. The study revealed that four factors have a positive impact on productivity, namely: (1) motivation to participate in any activity; (2) good social relationship; (3) achievement; and (4) the effort exerted to perform the task.

In summary, some researches showed the impact of motivation at the management level and others studied the construction workers aspects, but most of these studies relied on theories rather than empirical analysis. Moreover, many studies rely on expert opinions and perceptions rather than empirical data collected from construction sites. As a result, a key research gap in the construction domain is the lack of empirical studies linking motivation to productivity at the labor level. To address this knowledge gap, this study proposes a novel method for determining the relationship between worker motivation and productivity at construction sites.

3. Research Methodology

This paper aims to identify the relationship between labor motivation and the productivity through an empirical model. For the purposes of this research, two types of construction crafts for residential, industrial, and commercial projects are considered: brickworks and ceramic works crafts. This comprises measuring productivity, gathering motivation and productivity data, and predicting construction labor productivity using these data and advanced modelling techniques. To achieve the aim of this research, five stages were followed: identification of motivation factors affecting labor productivity; measuring motivation factors scores (weights); productivity measurement; productivity model development using artificial neural network (ANN) and multiple linear regression (MLR); validation of the models; and comparing the results of ANN and MLR models to select the best model. Fig. 1 depicts the research methodology procedures in five stages.

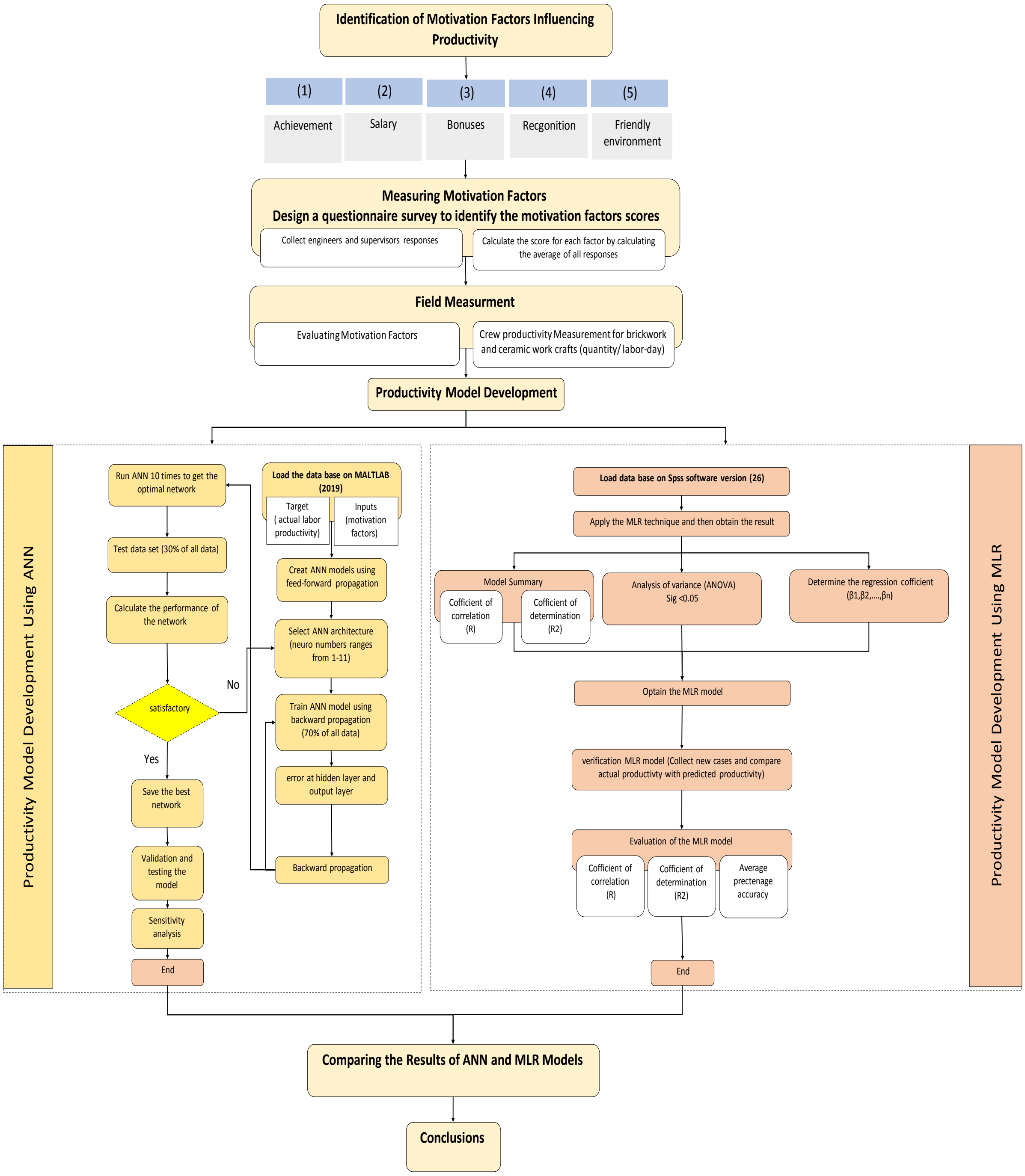

Fig.1. Research methodology framework.

3.1 Identification of motivation factors influencing productivity

The first stage in developing a productivity model is to identify motivation factors affecting Construction labor productivity. Numerous researches have been conducted to identify the motivation factors which affect labor productivity. Based on the literature, 14 factors were identified. 5 of which namely, salary, bonuses, achievement, recognition, and friendly environment are considered the critical factors. These factors were identified on the basis of a questionnaire survey and the responses of Egyptian engineers and labors. The factors were analyzed and ranked by using relative importance weight (RIW). Table 2 lists the identified factors and their relative importance weight.

Table 2. Motivation factors influencing labor productivity with their relative importance weight.

No	Factors	Author											Relative importance weight (RIW)
		Singh (2000)	Doloi (2007)	Venkatesan et al. (2009)	Dwivedula and Bredillet (2010)	Khan et al. (2011)	Shroff and Sridhar (2011)	Aarabi et al. (2013)	Afuye (2016)	Aghayeva and Ślusarczyk (2019)	Phan et al. (2020)	Gyamfi et al. (2020)	
1	**Achievement**	✓		✓			✓		✓				**0.078**
2	**Recognition**	✓	✓	✓			✓		✓	✓			**0.077**
3	Advancement	✓	✓	✓	✓			✓	✓	✓	✓		0.069
4	Growth	✓							✓				0.066
5	Training			✓		✓		✓		✓	✓	✓	0.061
6	Job security	✓	✓		✓				✓	✓		✓	0.074
7	Quality of supervision	✓							✓	✓			0.071
8	Safety programme								✓	✓			0.071
9	Quality of site management					✓				✓			0.066
10	**Salary**	✓				✓	✓	✓	✓	✓		✓	**0.078**
11	**Bonuses**					✓			✓	✓			**0.078**
12	Challenging task		✓						✓	✓			0.07
13	Freedom				✓	✓	✓	✓	✓				0.067
14	**Friendly environment**							✓	✓				**0.075**

3892

3.2 Data Collection

3.2.1 Measuring motivation factors

The five motivation factors were divided into qualitative and quantitative categories. Achievement, salary, friendly environment, and recognition were all regarded qualitative considerations, while bonus was a quantitative factor. To reduce the noise level in qualitative data, and to be able to measure and evaluate these factors, they have been divided into a set of subfactors that influence it. It was suggested that the quantitative factor represented by bonuses could be measured by the average of bonuses that labor can receive in his work. Table 3 shows the motivation factors and their subfactors.

A questionnaire was conducted to measure the factors. The questionnaire contains the major factors and their subfactors. It was required to identify the relevant score (relevant weight) of each sub factor, where the sum of the relevant scores of sub-factors for each factor must equal 100. Engineers and supervisors having sufficient experience were asked to participate in the questionnaire. The total number of questionnaires responded by engineers was 25 questionnaires, while supervisors were responded by 35 questionnaires. The relevant scores of the sub factors were calculated by taking the average of all responses. The motivation factors and its scores are presented in Table 4.

Table 3. Motivation factors and their sub factors.

Category	Factor			Sub factor	Reference
Qualitative factors	Achievement			Challenging work	Mansfield and odeh (1991)
				Work based on contract	Afuye (2016)
				Freedom to perform their tasks	singh (2000)
				Daily and weekly tasks are divided into small assignments	Adjei (2009)
				past evaluation	Singh (2000)
	Salary			Regularity of salary times	Afuye (2016) Opperman (2016)
				Average of salary	Opperman (2016)
				Fairness of payment	Phan et al. (2020)
	Recognition	Rewards	Intrinsic	Additional responsibility	Opperman (2016) Afuye (2016)
				Assigns challenging work	
				Public acknowledgement for work well done	Mansfield and odeh (1991)
			Extrinsic	Ensures good work conditions	Mansfield and odeh (1991)
				promotion	
				increase in salary for good work	
	Friendly environment			Working under pressure	Smithers and walker (2000)
				Respect between colleagues and project managers	Aarabi et al. (2013)
				Continuous communication with team	
		Safe and healthy environment		Safety plan	
				Employee training	
				Programme measurement and review (control)	
Quantitative factors	Bonuses			Very low	Opperman (2016)
				Low	
				Medium	
				High	
				High Very	

Table 4. Motivation factors influencing labor productivity with their scores.

Category	Factor			Sub factor	Score
Qualitative factors	Achievement			Challenging work	22
				Work based on contract	27
				Freedom to perform their tasks	16
				Daily and weekly tasks are divided into small assignments	21
				past evaluation	41
	Salary			Regularity of salary times	45
				Average of salary	30
				Fairness of payment	25
	Recognition	Rewards	Intrinsic	Additional responsibility	40
				Assigns challenging work	
				Public acknowledgement for work well done	
			Extrinsic	Ensures good work conditions	60
				promotion	
				increase in salary for good work	

Continue. Table 4. Motivation factors influencing labor productivity with their scores

Category	Factor		Sub factor	Score
Qualitative factors	Friendly environment		Working under pressure	18
			Respect between colleagues and project managers	30
			Continuous communication with team	28
		Safe and healthy environment	Safety plan	24
			Employee training	
			Programme measurement and review (control)	
Quantitative factors	Bonuses		Very low	20%
			Low	30%
			Medium	50%
			High	70%
			High Very	90%

3.2.2 Productivity and field measurement data collection

The researchers have identified that the most suitable method to collect data of factors and productivity is the direct method (Al-Zwainy et al., 2013). A work measurement form was designed to collect data from construction sites. Where the form included the motivation factors influencing productivity, and crew productivity. Brickworks and ceramic works crafts for residential, industrial, and commercial projects were considered. From five projects, 42 samples of brickwork and 48 of ceramic work were collected. First project was the diamond mole in El-mokattem city, total area is 35000 m^2; consisted of 10 parts. The second project was the development of the Chipsi Al -Obour Factory, total area is 90000 m^2. It consisted of two buildings, and each building consisted of four floors. The third project is wheat silos in the Zagazig city, consisting of 8 buildings, the building area ranges from 70 to100 m^2. The fourth and fifth project are one of the social housing projects in Egypt, their location in the cities of El-tagmoaa city and El-asher city respectively. The fourth project consisted of 15 buildings, every building had an area of 1250 m^2 and consisted of 6 floors, and a mosque of 5000 m^2, while the fifth project consisted of 10 buildings with an area of 900 m^2. Each influencing factor's status was recorded, and labor productivity was measured by dividing the total quantity achieved for the day by the number of labors on the crew.

4. Development of Productivity Models

In this study, both artificial neural network (ANN) and multiple linear regression (MLR) were used to develop a productivity model, in order to determine the relationship between labor productivity and motivation.

4.1 Development of Artificial neural network (ANN) model

4.1.1 Artificial neural network basics

The human brain is the most complex system in the world, having a large number of interconnected components. An ANN creates a mathematical model for a system by simulating the human brain. When the relationship between inputs and outputs is complex and cannot be explained precisely, this technique is extremely effective (Heravi and Eslamdoost 2015; Goodarzizad et al., 2021). The multilayer feed-forward neural network, trained with a back-propagation method, is a type of neural network that is widely used. The architecture form of this neural network is an input layer, one or even more hidden layers, and an output layer. The neurons in a feedforward neural network are only connected forward. Each layer of the neural network is connected to the layer next to it. Figure 2 represent the architecture of a three-layered feed-forward neural network with one hidden layer.

The training method for this type of neural network is known as back-propagation. Back-propagation is a controlled training method. When employing a training method, sample inputs and expected outputs must be presented to the network. For each input, the expected outputs are compared to the actual outputs. The back-propagation training algorithm takes the measured error and modifies the weights and the biases of the various layers backward from the output layer to the input layer using the expected outputs. The number of hidden layers and nodes in each layer cannot be determined using a specific approach. Several studies stated that the best architecture of the network could be determined using trial and error method (El-Gohary and Abdel-Khalek, 2017; and Al-A'amar, 2018). The number of nodes in the hidden layer could be calculated by using the following equation (AlZwainy et al., 2015).

$$Y= (2X_i+1) \quad (5)$$

Where: Y= maximum number of nodes in hidden layer; and X_i= number of inputs

The data in neural network is divided into two phases: training and testing. The learning process of the network is controlled by the training phase. The testing phase are used to assess the network's capacity to generalize. There aren't any rules determining the exact percentage assigned to the training and testing phases. Heravi and Eslamdoost (2015) divided the data into 70% for training and 30% for testing. El-Gohary and Abdel-Khalek (2017) used 75% for training. In the learning process, the weights of each input are calculated to generate the output of the next layer. The net weights presented in Eq. (6) are processed through the activation function to produce the output. The most prevalent multilayer network activation functions are hyperbolic tangent, sigmoid, and linear. Hyperbolic tangent was used in developing the neural network models by (Al-A'amar, 2018; and Goodarzizad et al., 2021). It is presented in Eq. (7)

$$X=\sum_{i=1}^{n} x_{iW_i} - b \quad (6)$$

Where n = the input number; x_i = the input value; and b = biases

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (7)$$

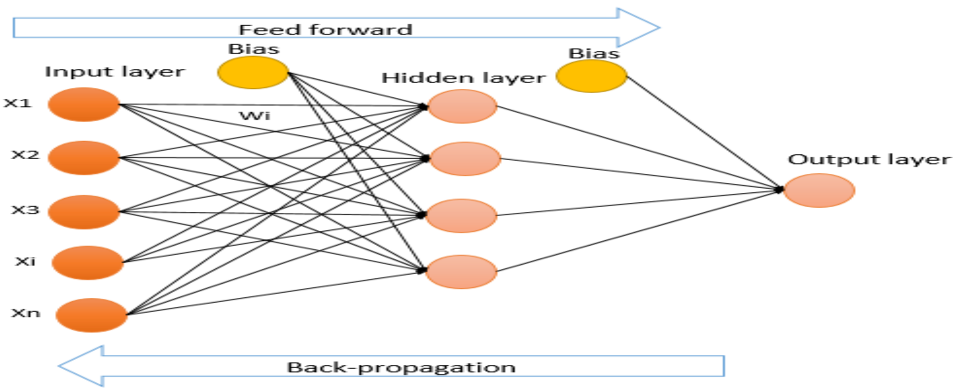

Figure 2. Graphical representation of the three-layer feedforward neural network architecture.

4.1.2 Developing the final ANN model

The productivity model was developed based on the 5 motivation factors. A simple ANN model was used to explore the influence of the motivation on the construction labor productivity. A multilayer feed-forward neural network trained by a back-propagation algorithm with one hidden layer was used. MATLAB 2019 software was used to develop the neural network model. In this study 70% of the data was used for training and 30% for testing. The number of nodes in hidden layer was identified with trial and error. The number of nodes must increase until there is no significant improvement in the model performance. The number of nodes ranges from 1 to 11, based on compensation in the [Eq. (6)]. The network performance is evaluated through the statistical parameters, i.e., coefficient of correlation (R), and the mean square error (MSE), which is expressed in Eq. (8). For the network architecture of brickwork and ceramic work, 10 iterations were generated for each architecture**.** A total of 220 networks were generated by increasing the number of nodes in the hidden layer from 1 to 11. Choosing the best network architecture is based on the combination of the highest value of the coefficient of correlation (R) and the minimum value of the mean square error (MSE). The statistical parameters of R, and MSE for training, testing, and all data for brickwork and ceramic work are represented in figures 3,4 respectively. According to the brickwork statistical parameters, a network with a hidden layer of 9 neurons is considered the best architecture. In networks with 9 neurons, MSE for all data has the minimum value among other networks, and the R value is 0.99, which is considered the maximum value. Figure 4 reveals that the best ANN architecture is a network of 10 neuros in the hidden layer. It reveals the best performance, where the minimum values of MSE is 0.012 for training, testing, and all data, and the R-value is 0.999 for training, testing, and all data

$$MSE=\frac{1}{N}\sum_{i=1}^{N}(A_i-P_i)^2 \qquad (8)$$

Where A_i = actual productivity; p_i = predicted productivity; N= number of data of each studied craft.

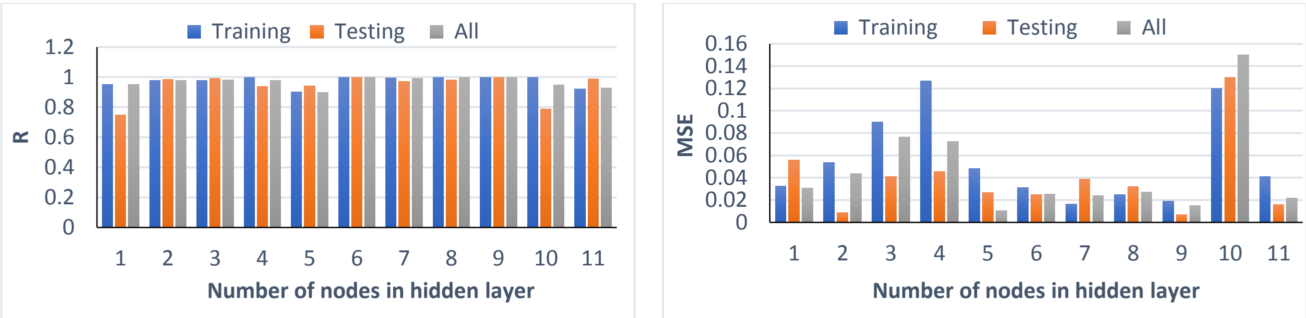

Figure 3. R and MSE values for each number of nodes in hidden layer for brickwork craft.

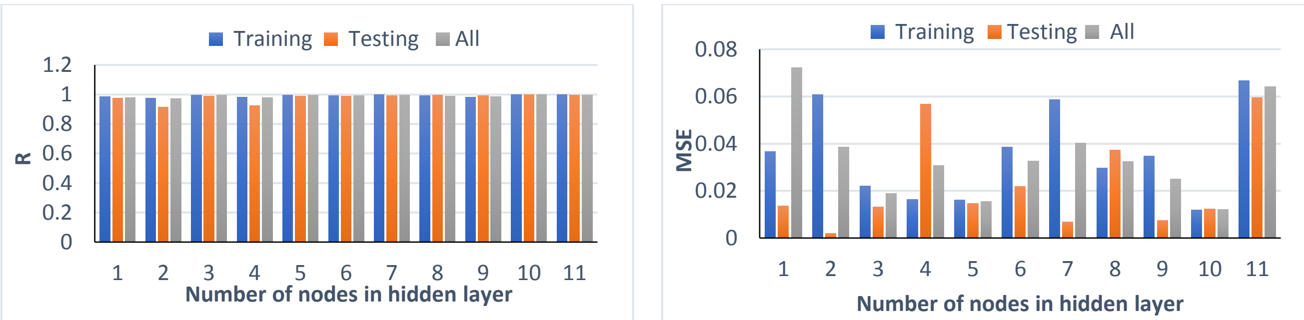

Figure 4. R and MSE values for each number of nodes in hidden layer for ceramic work craft.

4.1.3 Validation and testing of productivity models

For an illustration of the productivity model's validation and testing, a comparison between predicted and actual productivity for brickwork and ceramic work is shown in figure 5,6. As shown in the figures, the predicted and actual productivity values are extremely similar to each other, and the proposed ANN model can accurately predict labor productivity. Also, regression graphs for training, testing, and all data are shown in figures 7,8 for future analysis. R-values for training, testing, and all data in both crafts are 0.999, demonstrating a significant correlation between actual and predicted productivity.

To estimate the model's accuracy, the absolute difference between predicted and actual productivity for each data point was calculated and then divided by actual productivity. As a result, the following equation might be used to calculate the average accuracy percentage (AAP) of predicted productivity for all of the different crafts studied.

$$AAP\ (\%) = 100-\frac{\sum_{i=1}^{i=N}\sqrt{\frac{(Ai-Pi)^2}{Ai}}}{N} \qquad (9)$$

The average percentage accuracy of the ANN model of brickwork and ceramic work was 86.17%, and 86.89% respectively. This percentage reflects the model's validity, and indicates that increasing the accurate input amount of data can enhance output accuracy.

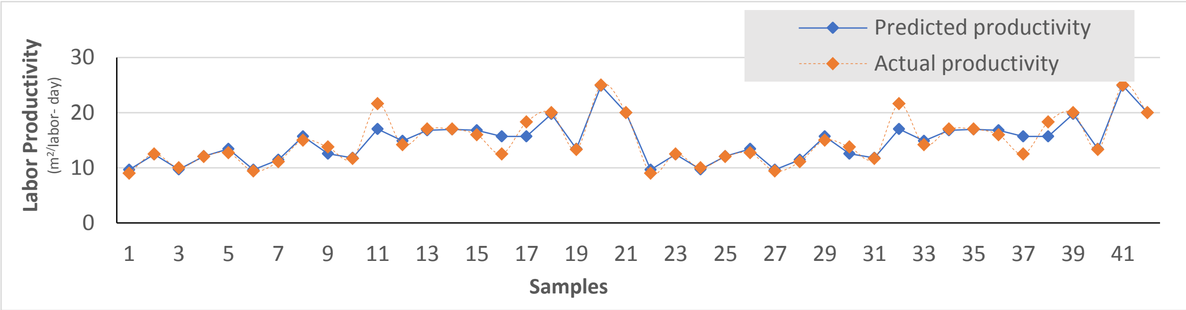

Figure 5. comparison between ANN predicted productivity and actual productivity for brickwork craft.

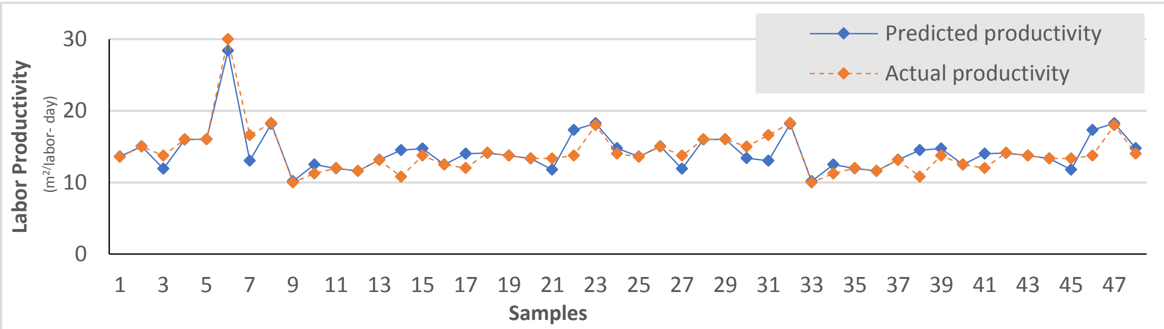

Figure 6. comparison between ANN predicted productivity and actual productivity for ceramic work craft.

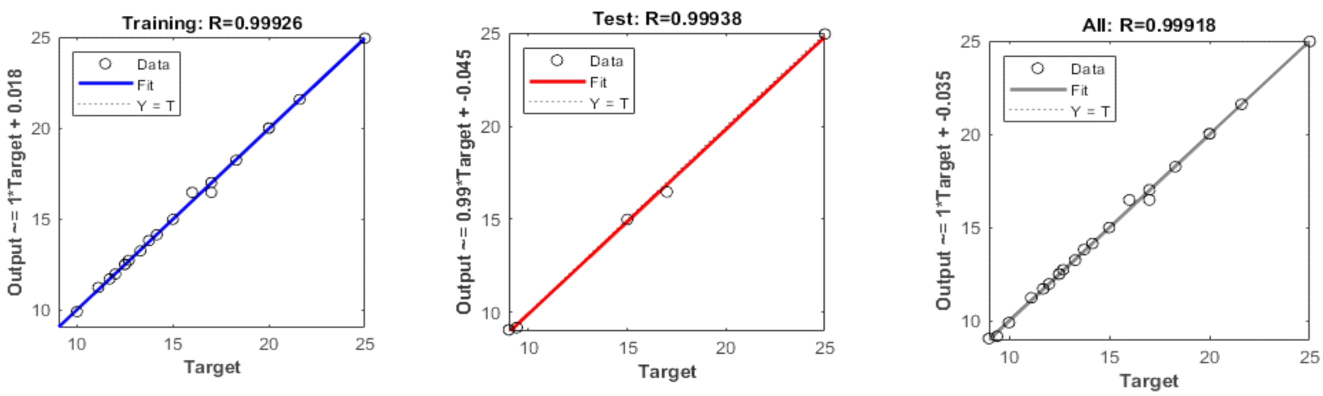

Figure 7. Regression plots for training, testing, and all data for brickwork craft.

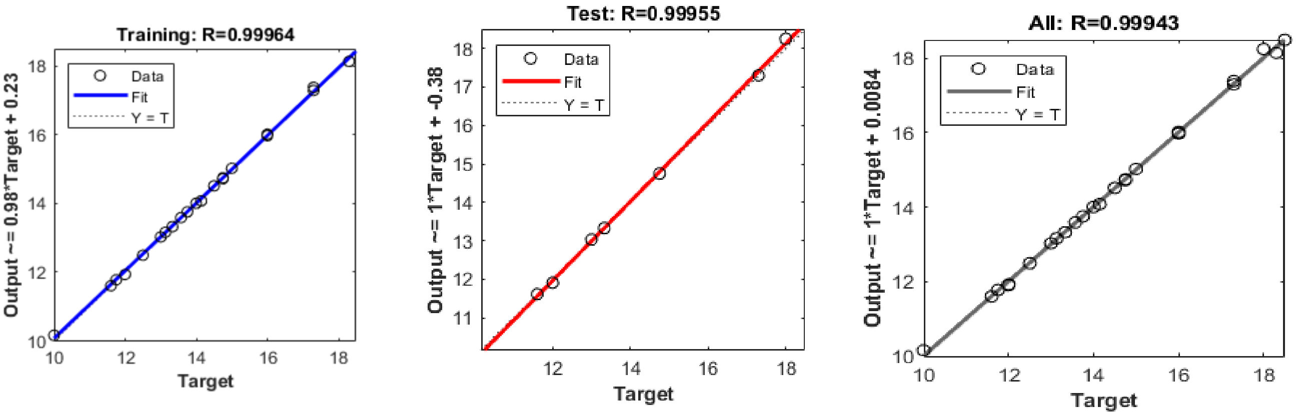

Figure 8. Regression plots for training, testing, and all data for ceramic work craft.

4.1.4 Sensitivity analysis

A sensitivity analysis was performed to show the impact of motivation factors on labor productivity in order to highlight the labor productivity improvement trend. As a result, each factor's affecting rate could be calculated. According to Sonmez and Rowings (1998), sensitivity analysis can be performed by changing the value of each factor while the values of the other factors are fixed. The sensitivity analysis included five factors namely, achievement, salary, bonuses, recognition, and friendly environment. It was conducted for brickwork craft. The maximum and minimum labor productivity can be established at the maximum and minimum ranges of the factors. the values of each factor are increased from 10 to 50, while other factors are fixed, and the influence rates of factors are established by running the network for each factor. The results of the analysis are shown in figure 9. It indicates that the factors have a positive influence on labor productivity, and any increase in their values improves labor productivity. Increasing the values of achievement, salary, bonuses, recognition, and friendly environment leads to approximately 24.2%, 14.8%, 5.7%, 34.6%, and 21.8% increase in labor productivity respectively.

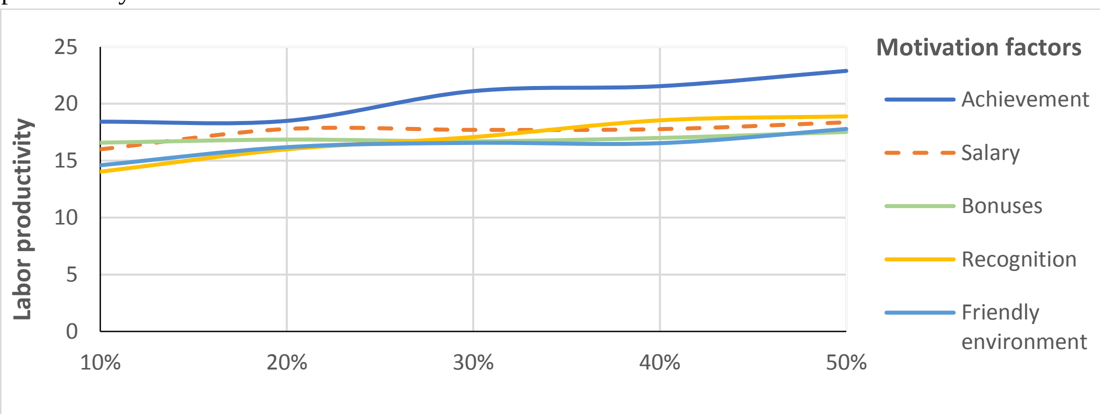

Figure 9. Sensitivity analysis results for brickwork craft

4.2 Development of the Multiple Linear Regression (MLR) Model

Multiple linear regression (MLR) is the most extensively used type of regression and is the most widely utilized form for predicting construction productivity by including project variables into a mathematical model. Multiple linear regression will be utilized in this case to determine the statistical relationship between motivation factors (independent variables) and labor productivity of brickwork and ceramic work crafts (dependent variable). The equation of multiple linear regression is:

$$Y_i = \beta_O + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_p X_p \quad (10)$$

Where i = 1, 2, 3, …., n; $Y_{i=}$ depended variable; X_1, X_2, X_3, ……, X_p = independent variables; $\beta_O, \beta_1, \beta_p =$ the coefficient in the relationship.

Statistical Software Package SPSS version (26) was used to develop two models for brickwork and ceramic work, and the results of the regression analysis can be concluded in the following tables, Table 5 illustrated the model summary, which contains the coefficient of correlation (R), and the coefficient of determination (R^2). The value of R for brickwork and ceramic work is 0. 922 and 0.745, respectively, which explain a very high correlation between motivation factors and labor productivity.

Table 5. Model summary for brickwork and ceramic work crafts.

Craft	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Brickwork	1	0.922	0.851	0.830	1.73493
Ceramic work	2	0.745	0.555	0.502	2.71245

Table 6 includes the analysis of variance. The F-statistics have a significance equal to 0.000 < 0.05, which supports the statistical model MLR's strong explanatory, and indicates a significant relationship between the motivation factors and labor productivity for brickwork and ceramic work crafts.

Table 6. Output of Analysis variance ANOVA for different crafts.

Crafts		Sum of Squares	df	Mean Square	F	Sig
Brick work	Between Groups	618.355	5	123.671	41.087	0.000
	Within Groups	108.359	36	3.010		
	Total	726.715	41			
Ceramic work	Between Groups	385.050	5	77.010		
	Within Groups	309.010	42	7.357	10.467	0.000
	Total	694.060	7			

Tables 7 includes the coefficients of regression, and statistical significance of independent variables on the dependent variable according to the results of brickwork and ceramic work models. The results show that the five motivation factors have a significant impact (sig <0.05) on the labor productivity. Based on the coefficients of regression, the MLR models of brickwork and ceramic work can be identified as shown in [Eq. (11), (12)].

Table 7. MLR analysis results for brickwork and ceramic work models.

Independent variables	Brick work craft			Ceramic work		
	Unstandardized Coefficients			Unstandardized Coefficients		
	B	Std. Error	Sig	B	Std. Error	Sig
Constant	-2.130	2.100	0.317	-8.779	3.796	0.026
Achievement	0.160	0.03	0.003	0.126	0.041	.004
Salary	0.178	.041	0.000	0.115	0.028	0.000
bonuses	.030	0.058	0.606	0.027	0.094	0.686
Recognition	0.287	0.018	0.000	0.27	0.20	0.036
Friendly environment	0.111	0.051	0.000	0.109	0.066	0.000

Y_1= -2.130+0.16 X_1+ 0.178 X_2 + 0.030 X_3 + 0.287 X_4 + 0.111X_5 (11)

Y_2= -8.779 + 0.126 X_1+ 0.115 X_2 + 0.027 X_3 + 0.27 X_4 + 0.109X_5 (12)

Where Y_1 = predicted productivity of brickwork (m^2/ labor-day); Y_2= predicted productivity of ceramic work (m^2/ labor-day); X_{1-5} are independent variables: X_1: achievement; X_2: salary; X_3: bonuses; X_4: recognition; X_5: friendly environment.

4.2.1 MLR model Verification

The verification's objective is to examine the accuracy and effectiveness of the MLR model. New data was collected to assess the model by comparing the results with actual productivity of brick work and ceramic work crafts. 5 new observations for each craft were collected from new project in el-sadat city, total area is 8367 m^2 as shown in Table 8.

Table 8. Number of observations of each variable.

Variables	Number of observations									
	Brick work					Ceramic work				
	1	2	3	4	5	1	2	3	4	5
Achievement	60	50	32	35	18	62	84	78	52	52
Salary	45	35	36	35	18	45	18	81	71	73
Bonuses	20	20	50	20	30	20	30	30	30	30
Recognition	45	60	36	32	8	66	8	8	52	38
Friendly environment	12	12	36	32	34	12	12	34	32	12

The predicted productivity of brickwork and ceramic work crafts can be calculated by using [Eq. (11, 12)] to each observation, and the results are presented in Table 9.

Table 9. Actual and predicted productivity for brickwork and ceramic work crafts.

	Brickwork			Ceramic work		
Observations	Actual productivity	Predicted productivity	ABS (A-P)/A	Actual productivity	Predicted productivity	ABS (A-P)/A
1	17	21.279	0.25170	13.33	15.191	0.13961
2	15	20.104	0.34026	11.75	8.806	0.250553
3	20	23.498	0.1749	17.3	21.235	0.227457
4	20	21.146	0.0573	18	21.065	0.170278
5	13.3	14.528	0.09233	14.75	14.369	0.025831
			∑0.9165			∑0.813728

38900

The average accuracy percentage (AAP) can be calculated by using [Eq. (9)]. The (APP%) were found to be 81.6 %, and 83.7% for brickwork and ceramic work, respectively, and the coefficient of correlation (R) is 0.99 for both crafts. Thus, it can be stated that the MLR model indicates good correlation with the actual measurements.

Discussion

The results obtained demonstrated the capability of the MLR and ANN to predict labor productivity, and to identify the relationship between labor motivation and productivity. in order to compare the findings of the two techniques, the results of the MLR and ANN are illustrated in table 10. The results showed that the ANN technique have the best results than the MLR techniques. However, these findings show that there is no appreciable difference between the two techniques' average levels of accuracy. The two models' high levels of accuracy can be explained to the strong correlation between labor motivation and construction productivity.

Table 10. Comparison of the results of ANN and MLR techniques.

Crafts	Technique	R%	R^2%	AAP%
Brickwork	ANN	99.9%	99.8%	86.17%
	MLR	99%	98.01%	81.6%%
Ceramic work	ANN	99.9%	99.8%	86.89%
	MLR	99%	98.01%	83.7%

According to the sensitivity analysis of ANN and the analysis of variance of MLR, the five motivation factors have a sufficient impact on productivity. The results demonstrated that the achievement might have an impact on productivity of up to 24%. Achievement is related to successfully completing challenging tasks and responsibility for completing tasks on schedule. The feeling of completion of tasks generates more energy and enthusiasm inside the labor, which increases productivity. The salary seems to be effective in increasing labor productivity. The results showed that increasing salary leads to Approximately14% changes in productivity. If the labor is satisfied with his salary, he can exert more effort and doing his job efficiently. Bonuses is showed to have a low effect on productivity, less than 5%. The ineffectiveness of the bonuses can be explained by the fact that the construction companies in Egypt almost don't apply incentive programmes for labors. According to the analysis, Recognition and friendly environment have an impact of 21 and 34% on productivity, respectively. it emerges that when managers appreciate the labor efforts, and when they have an appropriate work environment, workers are more enthusiastic to carry out their jobs, then productivity increases. It is suggested that construction companies should apply motivational programmes to boost labor productivity.

Conclusions

The aim of this study was to create ANN and MLR models for identifying the relationship between labor motivation and their productivity in construction projects. Based on the literature, 14 factors were identified, and a questionnaire was conducted to determine the critical motivation factors affecting labor productivity. This resulted in 5 factors namely, salary, bonuses, achievement, recognition, and friendly environment. A Questionnaire survey was conducted to engineers and supervisors to determine the relevant score of each factor. Labor productivity was studied in the brickwork and ceramic work crafts. From five projects, 42 samples of brickwork and 48 of ceramic work were collected. Then, ANN and MLR models were developed. The results indicted the capabilities of the two models in predicting labor productivity and identifying the relationship between labor motivation and productivity, but the results showed that the ANN performed the best, as its accuracy was the highest. To identify the impact of motivation factors on labor productivity, a sensitivity analysis was conducted. The results indicate that the five motivation factors have a positive influence on labor productivity. The analysis of variance (ANOVA) in MLR model also, proved the positive relationship between labor motivation and productivity, where the value of significance is equal to 0.000 < 0.05. Improving theses five critical factors can significantly boost labor productivity for construction projects.

References

Aarabi, M. S., Subramaniam, I. D., and Akeel, A. B. A. A. B, "Relationship between motivational factors and job performance of employees in Malaysian service industry". Asian Social Science, 9(9), 301, 2013.

Adjei, E. A. G., "Motivational strategies to improve productivity in the construction industry in Ghana", Ph.D. Thesis, 2009.

Afuye, F. U. N. S. O., "Motivation and its impact on workers' productivity in construction firms in Lagos, Nigeria." PhD diss., Kenyatta University,2016.

Aghayeva, K., and Ślusarczyk, B., "Analytic hierarchy of motivating and demotivating factors affecting labor productivity in the construction industry": the case of Azerbaijan. Sustainability. 11(21): 5975, 2019.

Al-A'amar, H. M., "Predicting Construction labour Productivity Using Optimal Artificial Neural Network, Multiple Linear Regression Models: Comparative Study", Ph.D. Thesis, 2018.

Al-Zwainy, F. M. S., Abdulmajeed, M. H., and Aljumaily, H. S. M., "Using multivariable linear regression technique for modelling productivity construction in Iraq", 2013.

Alzwainy, F. M. S., Al-Suhaily, R. H., and Saco, Z. M., "Project management and artificial neural networks: Fundamental and application". LAP LAMBERT Academic Publishing, 2015.

Arditi, D., and Mochtar, K., "Trends in productivity improvement in the US construction industry". Construction Management and Economics, 18(1), 15-27, 2000.

Doloi, H., "Twinning motivation, productivity and management strategy in construction projects". Engineering Management Journal. 19(3): 30-40, 2007.

Dongho, K., "Employee Motivation: Just Ask Your Employees". Seoul Journal of Business, 12, 2006.

Du, J., Zhu, Q., Shi, Y., Wang, Q., Lin, Y., and Zhao, D., "Cognition digital twins for personalized information systems of smart cities: Proof of concept". Journal of Management in Engineering, 36(2), 04019052, 2020.

Dwivedula, R., and Bredillet, C. N., "Profiling work motivation of project workers". International Journal of Project Management. 28(2): 158-165, 2010.

El-Gohary, K. M., and Aziz, R. F., "Factors influencing construction labor productivity in Egypt". Journal of management in engineering, 30(1), 1-9, 2014.

El-Gohary, K. M., Aziz, R. F., and Abdel-Khalek, H. A., "Engineering approach using ANN to improve and predict construction labor productivity under different influences". Journal of Construction Engineering and Management, 143(8), 04017045, 2017.

Gomar, J. E., Haas, C. T., and Morton, D. P., "Assignment and allocation optimization of partially multiskilled workforce". Journal of construction Engineering and Management, 128(2), 103-109, 2002.

Goodarzizad, P., Mohammadi Golafshani, E., and Arashpour, M., "Predicting the construction labor productivity using artificial neural network and grasshopper optimization algorithm". International Journal of Construction Management, 1-17, 2021.

Gyamfi, T. A., Nana-Addy, E., and Asiedu, W. G., "Motivational Strategies to Improve Artisan's Productivity in the Construction Industry in Ghana". Journal of Building Construction and Planning Research. 8 (4): 285, 2020.

Heravi, G., and Eslamdoost, E., "Applying artificial neural networks for measuring and predicting construction-labor productivity". Journal of Construction Engineering and Management, 141(10), 04015032, 2015.

Hiyassat, M.A., Hiyari, M.A. and Sweis, G.J., "Factors affecting construction labor productivity": a case study of Jordan. International Journal of Construction Management. 16(2):138-149, 2016.

Jarkas, A. M., "An investigation into the influence of buildability factors on productivity of in situ reinforced concrete construction". PhD diss., University of Dundee, 2005.

Jarkas, A. M., and Bitar, C. G., "Factors affecting construction labor productivity in Kuwait". Journal of construction engineering and management, 138(7), 811-820, 2012.

Jean, H.M., John, B., and Carolyn, F., "Organizational behaviour in a Global Context. London, Prentice Hall", 2006.

Johari, S., and Jha, K. N., "Impact of work motivation on construction labor productivity. Journal of Management in Engineering", 36(5), 04020052, 2020.

Khan, A. R., Umer, M., and Khan, S. M., "Effect of basic motivational factors on construction workforce productivity in Pakistan", 2011.

Khan, M. S., "Methods of motivating for increased productivity". Journal of Management in Engineering, 9(2), 148-156, 1993.

KM, A. N., and Aswathi, M. P., "Labor productivity model for structural elements by varying buildability factors using multiple regression analysis", 2018.

Li, Y., Lu, Y., Cui, Q., and Han, Y., "Organizational behavior in megaprojects: Integrative review and directions for future research". Journal of management in engineering, 35(4), 04019009, 2019.

Mansfield, N. R., and N. S. Odeh., "Issues affecting motivation on construction projects. International Journal of Project Management". 9(2): 93-98, 1991.

Momade, M. H., and Hainin, M. R., "Review of sustainable construction practices in Malaysian construction industry". Int. J. Eng. Technol, 7(4), 5018-5021, 2018.

Momade, M. H., and Hainin, M. R., "Identifying motivational and demotivational productivity factors in Qatar construction projects". Engineering, Technology & Applied Science Research, 9(2), 3945-3948, 2019.

Nassar, Y. S., and Khaleel, T. A., "Building model to predict labor productivity using multiple linear regression technique for formwork concrete columns". Kufa Journal of Engineering, 10(2), 2019.

Opperman, A. G., "Supervisory motivational strategies to improve productivity of construction workers". PhD diss., Cape Peninsula University of Technology, 2016.

Phan, P. T., Pham, C. P., Tran, N. T. Q., LE, H. T. T., Nguyen, H. T. H., and Nguyen, Q. L. H. T. T., "Factors Affecting the Work Motivation of the Construction Project Manager". The Journal of Asian Finance, Economics, and Business, 7(12), 1035-1043, 2020.

Prokopenko, J., "Productivity management": A practical handbook. International Labour Organization, 1987.

Rose, T., and Manley, K., "Motivation toward financial incentive goals on construction projects". Journal of business research, 64(7), 765-773, 2011.

Shiru, M. S., Chung, E. S, Shahid, S., and Alias, N., "GCM selection and temperature projection of Nigeria under different RCPs of the CMIP5 GCMS". Theoretical and Applied Climatology, 141(3), 1611-1627, 2020.

Shroff, R. P., and Sridhar, S., "Study of motivators and demotivators affecting the performance of employees in the construction industry–an exploratory study". International Journal of Construction Management. 11(3), 49-66, 2011.

Singh, A., "Motivational assessment of construction engineers". In Construction Congress VI: Building Together for a Better Tomorrow in an Increasingly Complex World, 554-563, 2000.

Sivaraj, S., and Vidivelli, B., "Effective Productivity in Construction through Labour Management". International Refereed Journal of Engineering and Science (IRJES), 7(4), 46-55, 2018.

Smithers, G. L., and Walker, D. H., "The effect of the workplace on motivation and demotivation of construction professionals". Construction management and economics, 18(7), 833-841, 2000.

Sonmez, R., and Rowings, J. E., "Construction labor productivity modelling with neural networks". Journal of construction engineering and management, 124(6), 498-504, 1998.

Talhouni, B. T., "Measurement and analysis of construction labour productivity". PhD diss., University of Dundee, 1990.

Thomas, A. V., and Sudhakumar, J., "Critical analysis of the key factors affecting construction labour productivity–An Indian Perspective". International Journal of Construction Management, 13(4), 103-125, 2013.

Thomas, H. R., Maloney, W. F., Horner, R. M. W., Smith, G. R., Handa, V. K., and Sanders, S. R., "Modeling construction labor productivity". Journal of construction engineering and management, 116(4), 705-726, 1990.

Venkatesan, R., Varghese, K., and Ananthanarayanan, K., "Motivation and demotivation cause factors for engineers in construction organizations". In Proceedings for the 25th Annual ARCOM Conference. 145-153, 2009.

Yi, W., and Chan, A. P., "Optimizing work–rest schedule for construction rebar workers in hot and humid environment". Building and Environment, 61, 104-113, 2013.