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An Extensive Machine Learning-based Comparative Analysis for Mimicking Loss of Productivity as a Result of Change Orders

Eslam Mohammed Abdelkader[1], Moaaz El-Kabalawy[1], Ahmed Assad[2], Abobakr Al-Sakkaf*[2,3], Nehal Elshaboury[4]

[1]Structural Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt.
[2]Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, QC, Canada.
[3]Department of Architecture & Environmental Planning, College of Engineering & Petroleum, Ḥadhramout University, Mukalla, Yemen. Corresponding author E-mail: abobakr.al-sakkaf@mail.concordia.ca
[4]Structural Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt.

Abstract Construction is a complex process which is associated with lots of changes. This results in issuing change orders. Change orders have a significant negative impact on time, cost and quality of construction projects. Labor productivity is regarded as one of the main performance metrics to judge the efficiency of the construction process. The implications of change orders on labor productivity are difficult to evaluate. Moreover, traditional-based models often fail to deal with such kind of input-output relationships. As such, the present study introduces a set of machine learning-based models to evaluate the implication of change order on labor productivity. This includes multiple linear regression, hybrid particle swarm optimization-liner regression, back-propagation artificial neural network, Elman neural network, radial basis neural network, generalized regression neural network and Cascade forward neural network. The comparisons were conducted as per mean absolute percentage error (MAPE), mean absolute error (MAE) and root-mean squared error (RMSE). Results demonstrate that the radial basis function network outperformed the afore-mentioned machine learning models such that it achieved MAPE, MAE and RMSE of 2.447%, 0.0141 and 0.0279, respectively. Finally, the significances of the capacities of the machine learning models are evaluated using two-tailed student's t-tests.

Keywords Change orders; labor productivity; machine learning; radial basis function network; student's t-test

1. Introduction

Variations are very common in construction industry, which elevates it as one of the complex processes to simulate. Construction industry is one of the influential contributors of the gross domestic product (GDP) of countries, whereas it represents 7-10% of the GDP in the developed countries and 3-6% in the developing countries. A variation in construction projects is any deviation from the agreed well-defined scope and/or schedule of work which results in a change order. Change order is the platform that represents the formal representation of the modified contract agreement between the contractor and owner and becomes part of the project's documents. These deviations involve adding to or reducing the scope of project work or correcting or modifying an original design [1]. They exist based on the fact that construction schedules are always being compressed, and with fast-track construction, building is beginning before the final design is complete. This can lead to incomplete or inaccurate designs. Accordingly, Change orders have become an everyday occurrence in construction, and they are widely accepted by both owners and contractors that change orders have negative effects on aspects such as cost, quality, time, and organization.

The owner usually realizes that change orders affect the specific task, but usually does not understand the ripple effects on the whole project. The increased costs of change orders to contractors can be attributed to items such as material procurement, scheduling conflicts, rework, the breaking of project momentum, increased overhead, increased equipment costs, and decreased labor efficiency. Most of the items, that are materials, overhead, and equipment, can be relatively easy to quantify. However, quantifying the impact of change orders on labor productivity remains to be a challenging task, despite the reported findings of many studies and documented cases [2]. The implications of the change orders on construction projects and their effective management need to be evaluated and modeled such that these changes vary with respect to the location to the project, type of the project and type of the work. In view of the above, the present study utilizes a set of machine learning models to evaluate the implications of change orders on labor productivity.

Literature Review

Several studies were conducted to evaluate the labor and equipment productivities in construction projects. Muqeem et al. [3] developed a back-propagation artificial neural network model to forecast the labor production rates in construction industry. They investigated a set of factors namely; weather, availability of material and equipment, location of the project, site conditions and number of workers. The developed model achieved mean-squared error of 7.76% and 12.29% for training and testing, respectively. Moreover, they highlighted that availability of material and equipment are the most influential factors which affect labor productivity. AL-Zwainy et al. [4] presented an artificial neural network-based model to predict the labor productivity of marble finishing works for floors. The model was based on a set of factors which were: age, experience, number of labor, height of floor, size of marble tiles, weather conditions, availability of materials, etc. The developed model yielded mean absolute percentage error, average accuracy percentage and correlation coefficient of 9.1%, 90.9% and 89.55%, respectively. In addition to that, they highlighted that age, experience and number of labor contribute significantly to the labor productivity of marble finishing works for floors.

Warsito et al. [5] designed an artificial neural network-based model to simulate the productivity of hydraulic static pile driver in silt soil. They utilized 252 observations from four actual projects and simulation models to build the model. They highlighted that the developed model was capable of achieving an average validity percentage and standard deviation of 98.13% and 1.67%, respectively. Joshi and Shrestha [6] presented an artificial neural network model to predict the labor productivity during the concreting stage in building construction. They investigated some attributes such as floor height, number of labor during construction, temperature, equipment efficiency, etc. The proposed model provided mean-squared error of 0.17. Furthermore, they pointed out that the haulage of material within construction site, and equipment efficiency are the two most significant factors which influences the labor productivity.

Gerek et al. [7] utilized feedforward neural network and radial basis neural network to model the productivity of masonry crews based on 147 observations. They highlighted that the number of laborers, total experience of crew, over time are among the factors which affected the crew productivity. They stated that the radial basis neural network provided a better approach in modeling the crew productivity based on the mean absolute percentage error. Heravi and Eslamdoost [8] utilized multilayer feedforward neural networks to model the relationship between the labor productivity in construction projects and a set of influencing factors. They stated that Bayesian regularization provided better performance than stopping criteria especially in the case of small dataset. Moreover, they pointed out that site layout, labor competence and proper planning were the most influential factors in modeling the labor productivity.

Ok and Sinha [9] applied regression analysis and artificial neural network to estimate the daily productivity of earthmoving equipment. They utilized a set of attributes to build the model which were hauling distance, earth condition, weather conditions, site management efficiency, etc. They stated that the neural network model provided a better productivity estimation model than the multiple regression analysis model. Ibbs [10] studied the different types of construction change orders and their effect on labor productivity. Data from 162 construction projects were statistically analyzed and a series of three curves are presented in this paper, representing the impact that change has on the labor productivity for early, normal, and late timing situations. It was found that the specific type of change was to a certain extent not as important as the mere presence of change and the timing of that change.

Dimken and Sonmez [11] utilized artificial neural network model to estimate the required man-hours of formwork activity of reinforced concrete frame buildings based on 613 data points. The input variables were total slab area, total length of beams, total length of columns, etc. They pointed out the developed model provided a versatile and efficient approach to estimate the formwork total labor man-hours in reinforced concrete framed building projects. Panas et al. [12] developed multi-layer feed forward artificial neural network model to forecast the concrete pavement construction productivity. The working length and working width were the two input variables required to predict the productivity of concrete pavement operation. They studied different types of scaling functions. Moreover, they highlighted that the developed model outperformed the multiple regression analysis model. Thus, based on the previous conducted studies, most of them focused on modeling labor and equipment productivities in construction projects. However, there is lack of investigation of the implication of change order on labor productivity. Moreover, most of the previous studies utilized feed forward back propagation neural network to predict the future performance, which often suffers from local minima entrapment and premature convergence especially in the case of large and exhaustive search space problems.

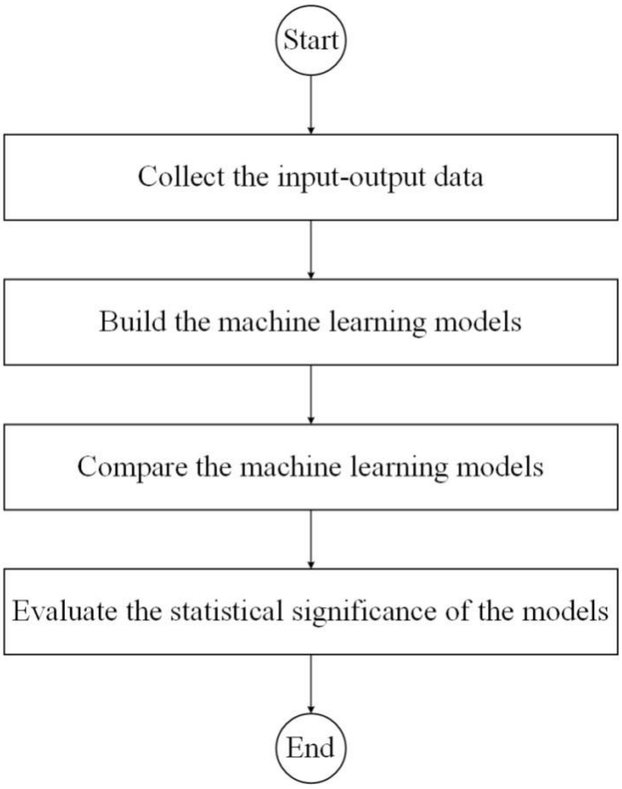

Figure 1: Framework of the proposed model

Proposed Method

The main objective of the present study is to develop an artificial neural network-based model to forecast the labor productivity loss caused by change orders. The framework of the proposed model is described in Figure 1. It is composed of four modules. The dataset used in the present study are 135 observations adopted from Assem [13]. The input variables used to build the prediction model are: work type, type of impact, number of change orders, frequency of change orders, average size of change orders, change order hours, ratio of change order hours to the planned hours and ration of change order hours to the actual hours. Work type can be architectural, civil, electrical or mechanical. The type of impact can be 1, 2 or 3 such that type of impact is equal to 1 when one cause of productivity loss takes place. Type of impact can be 2 or 3 when one or two additional major causes of change orders take place. Frequency of change orders is equal to the ratio of change orders number to the actual hours. Average size of change orders equals to the ratio of change order hours to the number of

change orders. The output of the model is the productivity loss which is expressed in the form of percentage such that it is equal to the ratio of non-productive hours to the actual direct hours worked.
Seven machine learning models are constructed and evaluated to forecast the loss of productivity. These models are: multiple linear regression, hybrid particle swarm optimization-liner regression, back-propagation artificial neural network, Elman neural network, radial basis neural network, generalized regression neural network and Cascade forward neural network. The neural network-based models are composed of eight input neurons for the previously-mentioned input variables and one output neuron for the loss of productivity. The performances of these models are assessed using split validation based on mean absolute error percentage error, mean absolute error and root-mean squared error. Eventually, two-tailed Student's t-tests were performed to evaluate the significance level of the outcome of the machine learning models [14].

Model Development
This section describes some of the models and algorithms presented in the "Proposed Method" section.

Hybrid particle swarm optimization-regression model (PSO-MR)
Regression analysis is a method adopted to establish a functional and mathematical relationship between a set of independent variables and dependent variables. The independent variable is sometimes called "response" while the dependent variable is sometimes called "predictor" [15].

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \ldots\ldots \beta_n x_n \quad (1)$$

Where;
y denotes the dependent variable. $x_1, x_2, x_3, \ldots\ldots x_n$ stand for the independent variables. β_0 is a constant. $\beta_1, \beta_2, \beta_3, \ldots\ldots \beta_n$ are the coefficients, which are computed using the least square method. In this model, particle swarm optimization algorithm is utilized to optimize the coefficients of the multiple regression analysis model by minimizing the mean absolute percentage error.
Meta-heuristics are bio-inspired optimization algorithms that are usually applied to solve complex and large exhaustive search space problems. They are characterized by their capabilities to overcome the shortcomings of inferior accuracy, local minima and premature convergence of hill-climbing derivative-based algorithms [16]. Particle swarm optimization (PSO) algorithm is a population-based meta-heuristic algorithm which simulates the social behavior of flocking birds. It was introduced by Eberhart and Kennedy in 1995. In it, particles modify their position based on its own best flying experience and the experiences of its companions [14, 17].
Each particle in the swarm is defined by its velocity and position. Over the course of optimization process, the velocity and position of the particle are updated iteratively. The velocity and the position of the particles are updated using the following Equations.

$$v_i(t+1) = w \times v_i(t) + c_1 \times r_1 \times (pbest_i(t) - x_i(t)) + c_2 \times r_2 \times (gbest_i(t) - x_i(t)) \quad (2)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (3)$$

Where;
$x_i(t+1)$ denotes the updated position vector of the particle I in the swarm. $x_i(t)$ stands for the current position vector of the particle i. $v_i(t+1)$ denotes the updated velocity of the particle i. $v_i(t)$ represents the current velocity of the particle i. r_1, and r_2 denote two uniformly distributed random numbers in the interval [0, 1] whereas they amplify the capability of searching for better solutions along the direction which is guided towards the global best, and the personal best. c_1, and $c_2$represent two constants and they refer to the cognitive learning, and social parameters and they control the effect of personal and global guides. Normally, c_1, and c_2 are assumed 2. w refers to the inertia weight which is utilized to manage the balance between the global and the local experience. A typical range of the inertia weight is between 0.3, and 0.7. It is recommended to start the search process with a large inertia weight at the beginning, and it decreases over the course of iterations using a damping factor to enhance the global exploration of the search space.

Feed forward neural network (FFNN)

A neural network is defined as a parallel distributing paradigm between input layer, output layer, and one or more hidden layer that are connected by neurons. Each neuron in the input layer receives one or more inputs and generates an output using a transfer activation function. Each neuron in the hidden layer receives output from all the input layers which equals to the weighted sum of all neurons entering the neuron. There is a weight assigned for each connection between neurons. The most common transfer or activation function is sigmoid function and it can be mathematically expressed using Equation (4) [18-19].

$$h_j = F(x_j) = \frac{1}{1 + e^{-x_j}} \tag{4}$$

Where;

x_j represents the weighted sum of all neurons entering the hidden neuron.

The input into the output layer should be also transformed using the sigmoid activation function. The error function at the output neuron between the actual and predicted values should be minimized and it can be calculated using Equation (5).

$$E(W) = \frac{1}{2}\sum_{k=1} (d_k - O_k)^2 \tag{5}$$

Where;

$E(W)$ represents the error function. d_k and O_k represents the actual and predicted values, respectively.

Based on the gradient descent algorithm, the weights are adjusted during each training epoch (k) based on Equation (6), whereas the error partial derivative is computed during each training epoch. In this context, the weights are updated according to the error partial derivative and the learning rate [20].

$$W_{ij}(k+1) = W_{ij}(k) + \Delta W_{ij}((k) = W_{ij}(k) - \eta \times \frac{\partial E(k)}{\partial W_{ij}} \tag{6}$$

Where;

$\Delta\, W_{ij}((k)$ refers to the adjustment or increment in the weights (weight updates). $W_{ij}(k+1)$ and $W_{ij}(k)$denote the new (updated) and current (old) weights, respectively. Η denotes the learning rate. $\frac{\partial E(k)}{\partial W_{ij}}$ stands for the error partial derivative with respect to the weights.

Elman neural network (ENN)

Elman neural network is one of the recurrent neural networks that was introduced by Elman in 1990. The topology of the Elman neural network is depicted in Figure 2. It is composed of four layers which are: input layer, hidden layer, contest layer and output layer. Elman neural network is characterized by the additional context layer which is the feedback coming from the hidden layer, and it is used as an input to the input layer in the next iteration. The feedback loop allows the Elman neural network to learn and recognize the temporal patterns and spatial patterns. Each neuron in the hidden layer is connected to each neuron in the context layer through a constant weight value. As such, the number of neurons in the context layer is equal to the number of hidden neurons. Elman neural network is trained using the gradient descent algorithm, which is a back propagation supervised algorithm that computes the parameters of the network by minimizing the global error function [21-22].

Radial basis neural network (RBNN)

Radial basis neural network is a kind of feed forward neural network which adopts supervised learning for the purpose of simulating input-output relationship. It is characterized by its high prediction performance, more complex nature, and faster convergence with reference to multi-layer perceptron. Its topology consists of input layer, hidden layer with non-linear activation function and output layer. In this context, the input layer receives its input meanwhile the hidden layer carries out the non-linear transformation. Gaussian function is the transfer activation function. In it, the width and center significantly affect its performance. The weights of the radial basis neural network are obtained stepping on gradient descent algorithm through minimizing the mean-squared error between the actual and simulated values [23-24].

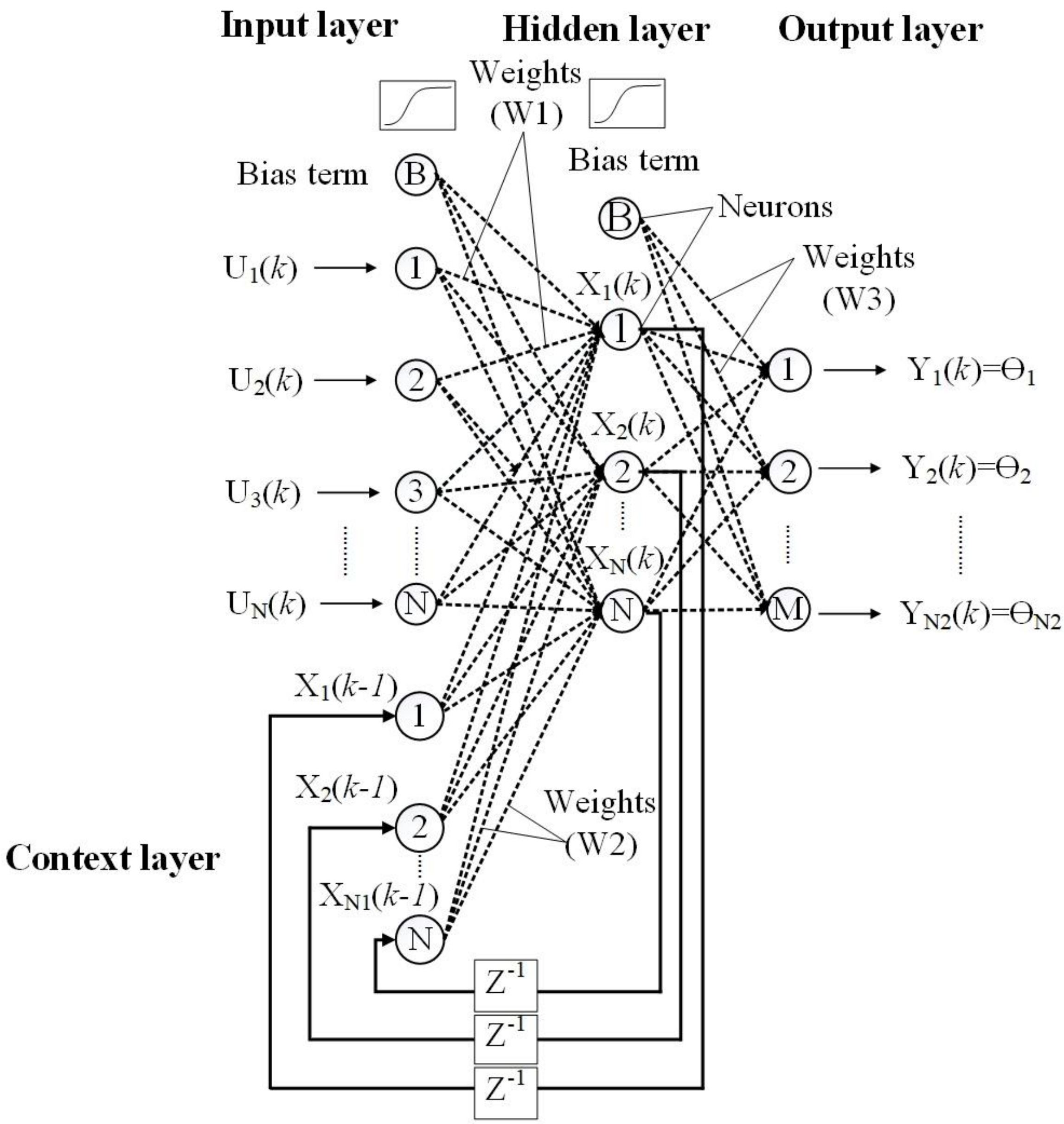

Figure 2: Architecture of Elman neural network

Generalized regression neural network (GRNN)

Generalized regression neural network is a kind of feed forward neural network that capitalizes on both normalized basis function and kernel regression. It utilizes probability functions for the sake of modeling the dependent variables. Generalized regression neural network does not get trapped in local minima resulting from its probabilistic nature. It comprises input layer, summation layer and output layer. The number of input neurons corresponds to the number of input variables. Gaussian function is the most commonly adopted activation function. There are two categories of summation layer namely, single division unit and summation unit. The spread parameter plays a fundamental role in the recognition capacity of generalized neural network. In this context, a smaller spread may undermine the learning capacity of the neural network while a larger one may smooth the function approximation [25-26].

Cascade forward neural network (CFNN)

The architecture of the cascade forward neural network is similar to the architecture of the feed forward neural network and updating the weights. However, each layer except the first layer has connecting weights coming from both the input layer and previous layers in the case of cascade forward neural network. As a result of presence of such kind of relationships between the layers, cascade neural network is capable of efficient linear and non-linear modeling in the input-output dataset [27-28].

Performance Indicators

The present study utilizes three performance indicators to compare between the four deterioration models. The three performance indicators are: root-mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). RMSE, MAE, and MAPE can be calculated using Equations (7), (8) and (9), respectively [29-30].

$$\mathrm{RMSE} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}(O_i - P_i)^2} \tag{7}$$

$$\mathrm{MAE} = \frac{1}{K}\sum_{i=1}^{K}|(O_i - P_i)| \tag{8}$$

$$\mathrm{MAPE} = \frac{100}{k} \times \sum_{i=1}^{K}\frac{|P_i - O_i|}{O_i} \tag{9}$$

Where;

O_i and P_i stand for the observed and predicted loss of productivity, respectively. K indicates number of observations.

Model Implementation

The dataset is comprised of 135 observations, whereas 114 data points are utilized for training while the remaining 21 data points are used for testing purposes. A sample of the data set required to build the loss of productivity prediction model is shown in Table 1. “Type_1” and “Type_2” represent type of work and type of impact, respectively. The terms “M”, “E”, “A” and “C” refer to the mechanical works, electrical works, architectural works and civil works. “No.” and “Freq.” stand for the number of change orders and frequency of change orders, respectively. “Av.size” stands for the average size of change orders. “Hours” stands for change order hours while “Loss of prod.” refers to loss of productivity occurred as a result of change orders.

Table 1: Sample of the loss of productivity data set [13]

Type_1	Type_2	No.	Freq.	Av.size	Hours	Hours/ planned hours	Hours/ Actual hours	Loss of prod.
M	1	24	0.94	97.13	2331	0.043	0.0405	0.086
M	1	5	0.19	738.2	3691	0.0683	0.0653	0.099
M	1	5	0.19	738.2	3691	0.0719	0.0653	0.1
E	1	39	9.58	25.36	989	0.0798	0.0712	0.11
M	1	98	3.71	90.1	8830	0.1285	0.1157	0.114
E	2	80	1.83	71.16	5692.5	0.1195	0.0973	0.19
E	2	59	2.45	219.27	12937.02	0.0959	0.0778	0.202
A	2	17	1.56	33.41	568	0.0841	0.0649	0.237
E	2	40	2.67	38.95	1558	0.2042	0.1657	0.239
A	2	34	1.37	165.03	5611	0.1116	0.0849	0.245
C	1	150	16.67	55.33	8300	0.1774	0.1562	0.1402
C	1	253	12.05	129.64	32800	0.4136	0.3374	0.1842
C	1	190	21.11	113.16	21500	0.4886	0.3772	0.2281
C	2	11	0.73	272.73	3000	0.0577	0.0475	0.1873

For the multiple linear regression analysis model, the developed mathematical function to forecast the loss of productivity is depicted in Equation (10).

$$y = -7.23 \times 10^{-2} + 8.29 \times 10^{-3} X_1 + 1.07 \times 10^{-1} X_2 + 1.16 \times 10^{-4} X_3 - 1.24 \times 10^{-3} X_4 - 1.15 \times 10^{-5} X_5 + 3.01 \times 10^{-7} X_6 + 3.01 \times 10^{-1} X_7 - 4.51 \times 10^{-2} X_8 \quad (10)$$

Where;

X_1, X_2, X_3 and X_4 refer to type of work, type of impact number of change orders and frequency of change orders, respectively. X_5, X_6, X_7 and X_8 stand for average size of change orders, change order hours, ratio of change orders hours to planned hours and ratio of change order hours to actual hours, respectively.

The second model is the hybrid particle swarm optimization-regression model, whereas particle swarm optimization algorithm is applied to optimize the coefficients of the multiple linear regression analysis model. The number of iterations is assumed 600, and the population size is assumed 300. The cognitive learning and social parameters are assumed two. The inertia weight is assumed 0.5. The convergence of the particle swarm optimization algorithm is shown in Figure 3. The minimum mean absolute percentage error achieved by the particle swarm optimization algorithm is 8.378%, which demonstrates its superior search capacity in exploring the parameter search space. A sample of the predicted values using the hybrid particle swarm optimization-regression model is shown in Figure 4. As shown in Figure 4, this model was capable of simulating the loss of productivity efficiently.

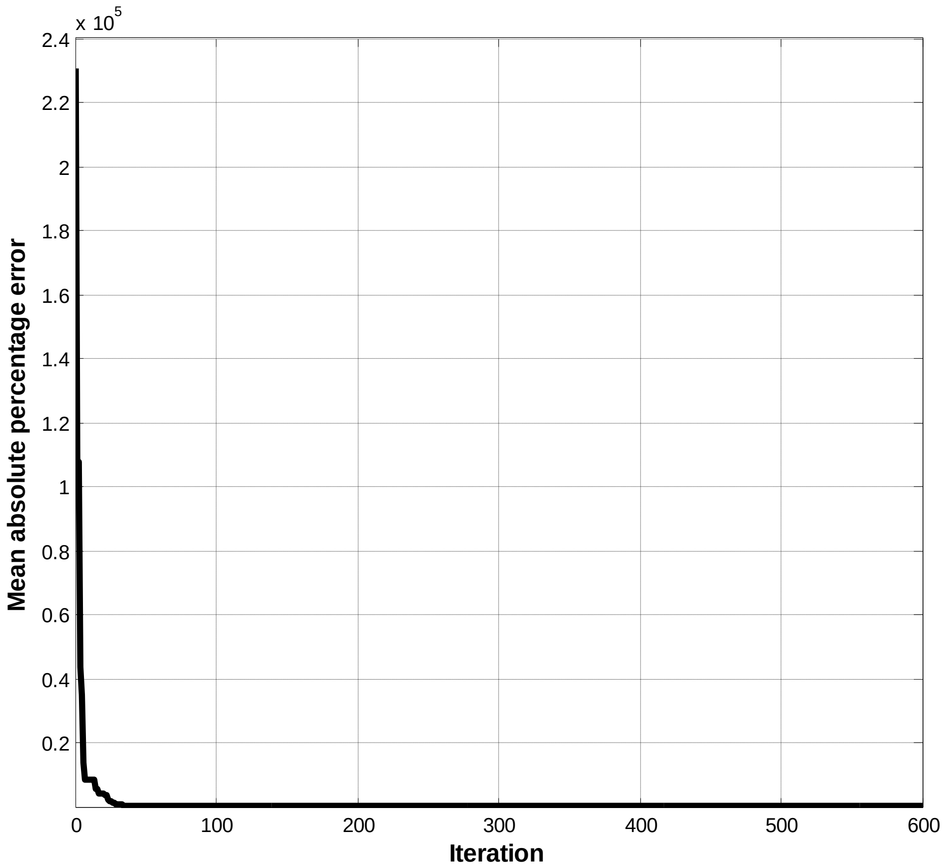

Figure 3: Convergence of the particle swarm optimization algorithm

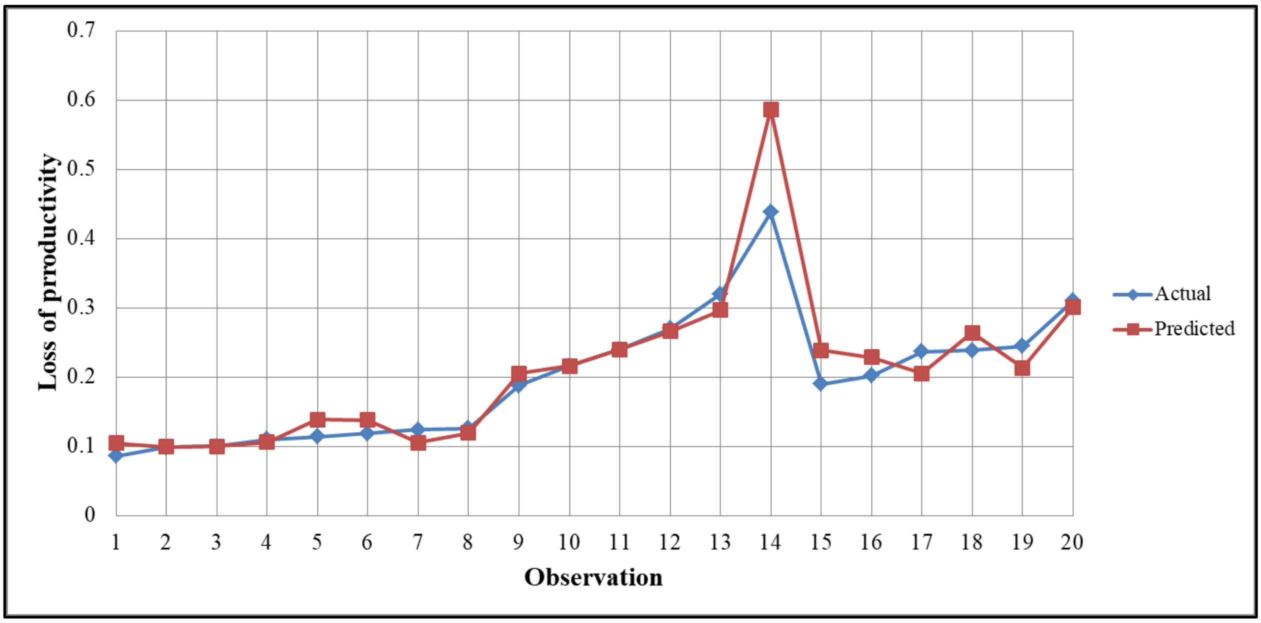

Figure 4: Actual and predicted values using the hybrid particle swarm optimization-regression model

For the feed forward neural network, the number of hidden layers, number of hidden neurons and momentum coefficient are assumed 5, 3 and 0.001, respectively. In the Elman neural network model, the number of hidden layers, number of context layers, number of hidden neurons and number of context neurons are assumed 4, 4, 3 and 3, respectively. For the radial basis neural network, the maximum number of neurons in the hidden layer is assumed 10 while the spread of the Gaussian activation function is assumed 1. In the generalized regression neural network, the spread of the Gaussian activation function is assumed 1. In the cascade forward neural network, the number of neurons in the hidden layer is assumed 10. A sample of 20 observations for the actual and predicted values using Elman neural network and cascade forward neural network model are presented in Figures 5 and 6, respectively. As shown in Figures 5 and 6, the Elman neural network model and cascade forward neural network can serve as efficient platforms to predict the loss of productivity. The predicted values of the testing dataset using the seven machine learning are shown in Table 2.

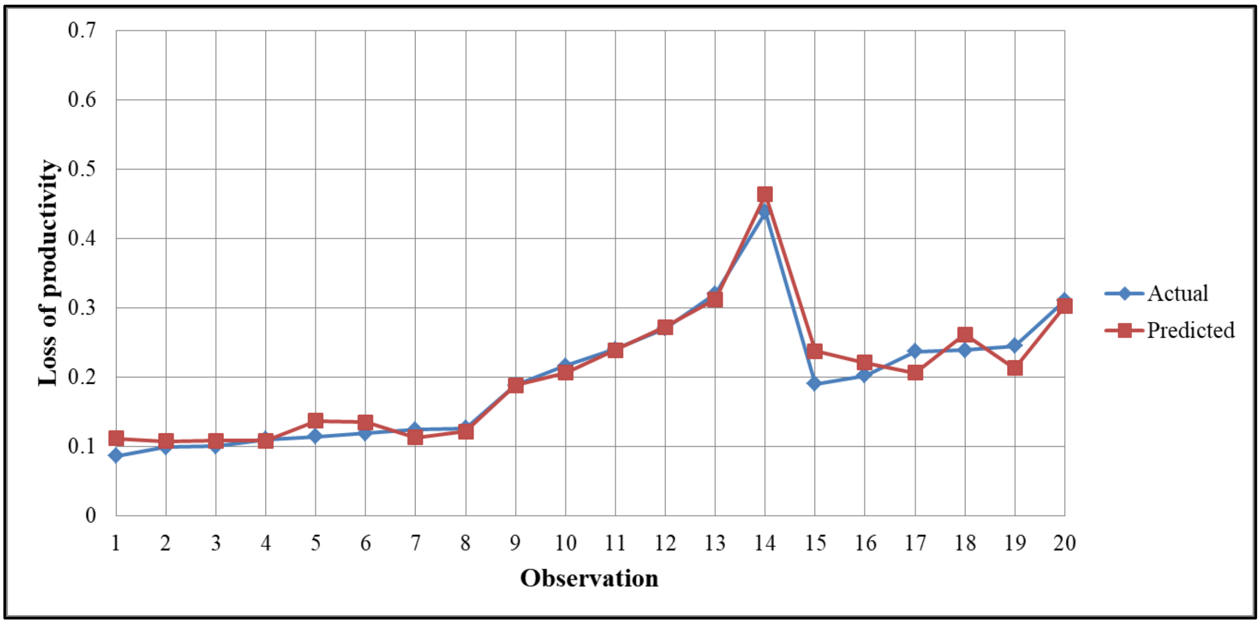

Figure 5: Actual and predicted values using Elman neural network model

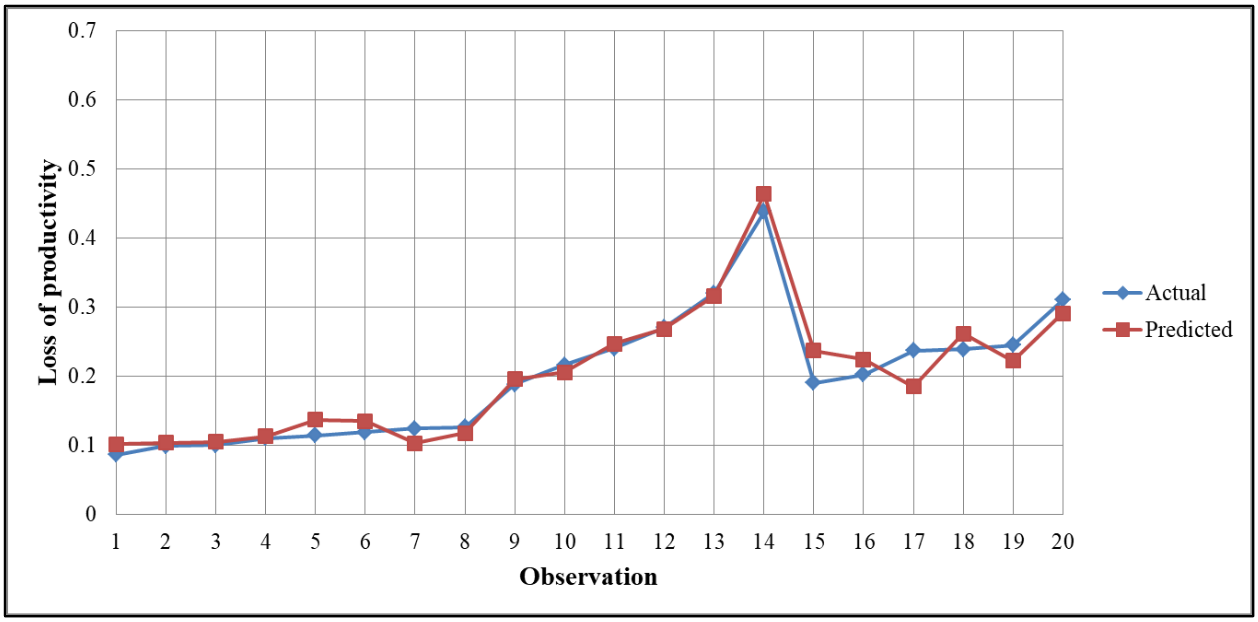

Figure 6: Actual and predicted values using Cascade forward neural network model

Table 2: Predicted values for the testing dataset using the seven machine learning models

ID	Actual value	MR	PSO-MR	FFNN	ENN	RBNN	GRNN	CFNN
1	0.3344	0.372	0.436	0.4058	0.3884	0.408	0.14	0.3811
2	0.318	0.2948	0.3338	0.3351	0.3300	0.3180	0.318	0.3191
3	0.2171	0.2109	0.2462	0.2422	0.2426	0.386	0.23	0.2456
4	0.2353	0.2393	0.2824	0.2875	0.2747	0.387	0.3085	0.2549
5	0.2978	0.2588	0.3078	0.3275	0.3076	0.398	0.2589	0.2849
6	0.3515	0.3117	0.3650	0.3864	0.3676	0.4132	0.3017	0.2797
7	0.32	0.2788	0.3154	0.3154	0.3174	0.321	0.32	0.3209
8	0.3351	0.3251	0.3642	0.3670	0.3524	0.4452	0.2946	0.3552
9	0.3693	0.3457	0.3849	0.3900	0.3608	0.4315	0.3396	0.3660
10	0.3697	0.3431	0.3783	0.3795	0.3628	0.4215	0.2958	0.3729
11	0.4049	0.3739	0.4148	0.3995	0.3847	0.413	0.2946	0.3987
12	0.4059	0.3832	0.4235	0.4049	0.3720	0.4234	0.168	0.4102
13	0.3509	0.3175	0.3556	0.3588	0.3518	0.4822	0.1101	0.3444
14	0.36	0.3023	0.3378	0.3416	0.3422	0.3621	0.36	0.3354
15	0.3631	0.3170	0.3703	0.4079	0.4422	0.408	0.3871	0.2400
16	0.384	0.2951	0.3402	0.3596	0.3702	0.3842	0.384	0.3604
17	0.393	0.3680	0.4048	0.3965	0.3913	0.3932	0.393	0.3937
18	0.408	0.3458	0.3926	0.3848	0.3826	0.4131	0.408	0.3762
19	0.4534	0.3694	0.4068	0.3970	0.3872	0.4163	0.2105	0.4039
20	0.4603	0.3644	0.4054	0.4397	0.4665	0.428	0.3017	0.0155
21	0.494	0.488	0.5291	0.4346	0.4555	0.4940	0.494	0.4962

A comparative analysis between the different machine learning models is described in Table 3. As shown in Table 3, MR model provided the least prediction performance. Moreover, PSO-MR outperformed the MR model, which evinces that coupling particle swarm optimization algorithm with multiple regression analysis model can enhance the prediction capacity of the multiple regression analysis model. For the artificial neural network models, Elman neural network achieved the best performance based on RMSE while cascade forward neural network achieved the least performance. Based on MAE, radial basis neural network yielded the highest prediction accuracy. On the other hand, cascade forward neural network provided the least prediction performance. Based on MAPE, radial basis neural network provided the least MAPE while feed forward neural network achieved the highest MAPE. In view of the above, multiple regression analysis model had the least prediction performance, whereas it achieved RMSE, MAE and MAPE of 0.0441, 0.0753 and 15.697%, respectively. Radial basis neural network provided the highest performance, whereas it attained RMSE, MAE and MAPE of 0.0279, 0.0141 and 2.447%, respectively.

Table 3: Comparative analysis of the machine learning models

Model	**RMSE**	**MAE**	**MAPE**
Multiple regression analysis model	0.0441	0.0753	15.697%
Hybrid particle swarm optimization-regression model	0.0299	0.0407	8.234%
Feed forward neural network	0.0248	0.0386	8.476%
Elman neural network	0.0232	0.0359	7.626%
Radial basis neural network	0.0279	0.0141	2.447%
Generalized regression neural network	0.0446	0.0238	3.682%
Cascade forward neural network	0.0475	0.0414	8.081%

Two-tailed Student's t-tests were performed to evaluate the significance level of the machine learning models' outcome, whereas the significance level (α) is set to be 0.05. The paired Two-tailed Student's t-tests for the machine learning models are depicted in Table 4. The performed student's t-tests examine the null hypothesis (H_0), which is that there is no significant difference between the capacities of the machine learning models. On the other hand, the alternative hypothesis (H_1) assumes that there is a significant difference between the capacities of the machine learning models. If the $P-\text{value}$ is less than the significance level, then the null hypothesis is rejected in favor of the alternative hypothesis. Nevertheless, if the $P-\text{value}$ is more than the significance level, thus the null hypothesis is accepted. As presented in Table 4, the pairs (MR, PSO-MR), (MR, FFNN), (MR, ENN), (MR, EBNN), (MR, GNN) and (MR, CFNN) are less than 0.05, which means that the null hypothesis (H_0) is false. Thus, there is a statistically significant difference between the pairs of the machine learning models. The $P-\text{value}$ of the pair (FFNN, GRNN) is more than 0.05, which highlights that there is no statistically significant difference between the machine learning models. Also, the radial basis neural network significantly outperformed all other machine learning models except the generalized regression neural network and cascade forward neural network. This proves its superior capability in serving as an efficient paradigm for modeling the loss of productivity caused by change orders.

Table 4: Statistical comparison between the machine learning models based on two-tailed Student's t-test

Pair of models	**MR**	**PSO-MR**	**FFNN**	**ENN**	**RBNN**	**GNN**	**CFNN**
MR	H_0 ($P-\text{value}$ =1)	H_1 ($P-\text{value}$ =4.71×10^{-2})	H_1 ($P-\text{value}$ =4.61×10^{-2})	H_1 ($P-\text{value}$ =4.58×10^{-2})	H_1 ($P-\text{value}$ =4.55×10^{-2})	H_1 ($P-\text{value}$ =4.7×10^{-2})	H_1 ($P-\text{value}$ =4.93×10^{-2})
PSO-MR	H_1 ($P-\text{value}$ =4.71×10^{-2})	H_0 ($P-\text{value}$ =1)	H_0 ($P-\text{value}$ =3.21×10^{-1})	H_0 ($P-\text{value}$ =1.01×10^{-1})	H_1 ($P-\text{value}$ =4.89×10^{-2})	H_0 ($P-\text{value}$ =6.69×10^{-2})	H_0 ($P-\text{value}$ =8.5×10^{-1})
FFNN	H_1 ($P-\text{value}$ =4.61×10^{-2})	H_0 ($P-\text{value}$ =3.21×10^{-}	H_0 ($P-\text{value}$ =1)	H_0 ($P-\text{value}$ =8.63×10^{-2})	H_1 ($P-\text{value}$ =4.28×10^{-2})	H_0 ($P-\text{value}$ =7.21×10^{-1})	H_0 ($P-\text{value}$ =4.73×10^{-1})
ENN	H_1 ($P-\text{value}$ =4.58×10^{-2})	H_0 ($P-\text{value}$ =1.01×10^{-}	H_0 ($P-\text{value}$ =8.63×10^{-2})	H_0 ($P-\text{value}$ =1)	H_1 ($P-\text{value}$ =4.97×10^{-2})	H_0 ($P-\text{value}$ =8.44×10^{-2})	H_0 ($P-\text{value}$ =2.26×10^{-1})
RBNN	H_1 ($P-\text{value}$ =4.55×10^{-2})	H_1 ($P-\text{value}$ =4.89×10^{-2})	H_1 ($P-\text{value}$ =4.28×10^{-2})	H_1 ($P-\text{value}$ =4.97×10^{-2})	H_0 ($P-\text{value}$ =1)	H_0 ($P-\text{value}$ =1×10^{-1})	H_0 ($P-\text{value}$ =5.32×10^{-2})
GRNN	H_1 ($P-\text{value}$ =4.7×10^{-2})	H_0 ($P-\text{value}$ =6.69×10^{-2})	H_0 ($P-\text{value}$ =7.21×10^{-1})	H_0 ($P-\text{value}$ =8.44×10^{-2})	H_0 ($P-\text{value}$ =1×10^{-1})	H_0 ($P-\text{value}$ =1)	H_0 ($P-\text{value}$ =7.08×10^{-2})
CFNN	H_1 ($P-\text{value}$ =4.93×10^{-2})	H_0 ($P-\text{value}$ =8.5×10^{-1})	H_0 ($P-\text{value}$ =4.73×10^{-1})	H_0 ($P-\text{value}$ =2.26×10^{-1})	H_0 ($P-\text{value}$ =5.32×10^{-2})	H_0 ($P-\text{value}$ =7.08×10^{-2})	H_0 ($P-\text{value}$ =1)

Conclusion

An intensive study was conducted to study the impact of change orders on construction productivity which is one of the major strategic components in determining the success or failure of a construction project and has a relationship with different factors. This study is based on a comprehensive literature review, and a comparative analysis among the different machine learning models to predict the implication of loss of productivity caused by change order. The investigated machine learning models are: multiple regression analysis, hybrid particle swarm optimization-regression, feed forward neural network, Elman neural network, radial basis neural network, and generalized regression neural network. Multiple regression analysis model provided the least prediction performance, whereas it achieved RMSE, MAE and MAPE of 0.0441, 0.0753 and 15.697%, respectively. On the contrary radial basis neural network attained the highest performance, whereas it attained RMSE, MAE and MAPE of 0.0279, 0.0141 and 2.447%, respectively. Eventually, the two-tailed Student's t-tests were performed to explore the statistical significance of the output provided by the different machine learning models. Accordingly, it is expected that the radial basis neural network can provide a solid paradigm for modeling the loss of productivity caused by change orders.

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