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APPLICATION OF SOFT COMPUTING TECHNIQUES TO PREDICT CONSTRUCTION LABOUR PRODUCTIVITY IN SAUDI ARABIA

*Ehab A. Mlybari

College of Engineering and Islamic Architecture, Umm Al-Qura University, Saudi Arabia,

*Corresponding Author, Received: 20 Dec. 2019, Revised: 12 March 2020, Accepted: 27 March 2020

ABSTRACT: Construction labour productivity is affected by a number of factors. In this study, multilayer perceptron neural network (MLPNN), support vector machine (SVM), general regression neural network (GRNN), and multiple additive regression trees (MART) methods were developed to estimate the labour productivity rates of concrete construction activities. Various soft computing techniques were used to examine their respective results to identify the best method for estimating expected productivity. The predictive behaviours of the different techniques are compared with those found in previous productivity studies. The results show that for predicting labour productivity for steel fixing and concrete pouring and finishing, the GRNN model outperforms the other techniques. The GRNN model provided improvements in the root mean square error (*RMSE*) of 199.41%, 23.21%, and 53.46% over MLPNN, SVM, and MART, respectively, for labour productivity of steel fixing, and 3,311.78%, 681.81%, and 776.68%, respectively, for labour productivity of concrete pouring and finishing. For predicting labour productivity for formwork assembly, the MART method was found to be the superior one, providing improvements in the *RMSE* of 232.93%, 90.89%, and 28.88% over MLPNN, GRNN, and SVM, respectively.

Keywords: Labour productivity, Construction projects, Modelling, Prediction.

1. INTRODUCTION

Construction has been one of the most active sectors of the Saudi Arabian economy in recent years, accounting for 5.12% of GDP. It has long been considered the third-largest non-oil sector in Saudi Arabia. In 2019, more than 5,200 construction projects are on-going in Saudi Arabia, representing a value of USD 819 billion, according to a report by BNC Network. The value of these projects' accounts for approximately 35% of the total value of active projects across the Gulf Cooperation Council. The Saudi Arabian construction market is expected to witness significant growth and offers lucrative potential because of its Vision 2030 plan, National Transformation Program (NTP 2020), and several on-going reforms to diversify its investments away from oil.

Labour productivity is a key issue in the construction industry because it affects any construction project's time and cost performance [1]. Liu and Ballard [2] argued that a project's financial success depends on labour productivity. Labour costs account for 30:60% of total project costs in most construction projects [3]. Labour performance is influenced by many factors and is usually associated with time, cost, and quality performance indicators. Several studies have been developed to recognize and rank factors affecting construction labour productivity. To realize the expected income from any construction project, it is vital to control the factors of productivity which contribute to the integrated production composition [2]. For this to be done effectively, quantifying the mapping relation between productivity rates and associated productivity factors is important [2]. The impact of various factors on the productivity of construction labour can be quantified using productivity models. There are numerous methods to analyse and measure the relationship between influential variables and the relevant rates of labour productivity. The models of expectancy and action–response to understanding productivity variations, but cannot be utilized to measure the effect on the productivity of multiple factors. In general, regression models are limited by the number of variables and their ability to quantify the combined effect of these factors [4]. Expert systems have very exceptionally abilities to recognize, map a function and generalize solutions [5]. Artificial neural networks (NNs) measure and map a function in the same manner that a human brain computes and has the same ability to learn from experience and enhance its efficiency. This investigation explores the use of the support vector machine (SVM), multiple additive regression trees (MART), general regression neural network (GRNN) and multilayer perceptron neural network (MLPNN) methods to predict the productivity rates of concrete construction activities.

2. LITERATURE REVIEW

2.1 Labour Productivity Factors

Several researches were carried out to establish the factors affecting labour productivity in construction projects. Herbsman and Ellis [6] examined the effects of the construction influencing factors on changes on the variance in productivity rates for construction items and developed a statistical model to explain how the influence factors and the productivity rates are related.

Sanders and Thomas [7] found that work type, structural element, construction methods, design specifications, and environment were the key elements affecting labour productivity in masonry work. Kaming, Olomolaiye, Holt, and Harris [8] examined factors affecting the productivity of craft workers in Indonesia and have decided that the most important are resource shortages, rework, the absently of employees, and the lack of appropriate equipment. Proverbs, Holt, and Olomolaiye [9] performed the comparative assessment between French, German, and UK construction contractors on the productivity rates of reinforcement fixing. Mohamed and Srinavin [10] argued that further to air temperature, relative humidity, and wind speed, additional thermal environment parameters should be considered in the study of the effects of the thermal environment on construction labours productivity in order to improve the predictive power of forecasts of construction labours productivity forecasts. Makulsawatudom, Emsley, and Sinthawanarong [11] have studied the essential factors that affect Thailand construction productivity. Abdul Kadir, Lee, Jaafar, Sapuan, and Ali [12] carried out a study on the critical factors influencing the productivity of construction labour for Malaysian residential projects. The effect of encouragement on the productivity of workers in the Nigerian construction industry has been studied by Aiyetan and Olotuah [13]. Furthermore, Alinaitwe, Mwakali, and Hansson [14] examined factors that affect craft workers productivity in Uganda. Enshassi, Mohamed, and Mayer [15] concluded that shortages of resources, lack of labour experience, lack of labour supervision, misunderstandings between labour and superintendents, and altering the drawings and specifications during implementation are the main factors negatively impact the labour productivity of construction project in Gaza. Ailabouni [16] conducted a study to identify factors affecting the productivity of an employee in the construction industry in the UAE. Singh [17] listed in four categories: industry-level, labour, site management, and external factors influencing the construction operations productivity for infrastructures and buildings in the UAE. Kheirieh and Heravi [18] identified and categorized into the four main groups 45 factors with the greatest impact on labour productivity in Iran's South Pars Gas Field development: external, managerial, human, and technical. Their results show the greatest impact of environment, management, encouragement and opportunities, resources, planning, and materials on labour productivity. Shehata and El-Gohary [19] researched the productivity of construction labour and presented it as a measure of construction project success. The relative significance of 45 factors that were perceived to labour productivity at Kuwait construction projects were described and indexed by Jarkas and Bitar [20]. With the aid of Eslamdoost and Heravi [21], a much greater in-intensity dialogue and literature review of surveys are given by defining and evaluating labour productivity factors. Jarkas [22] quantified the impact on construction productivity and established a practical approach to the relationship between relevant buildability factors and the productivity of formwork labour in building floors using a practical approach. Khaleel and Nassar [23] identified and analysed the factors which affect labour productivity in construction projects in the Arab world.

2.2 Soft Computing Techniques in Construction Productivity

Moselhi, Hegazy, and Fazio [24] cited the prediction of a productivity level realistic for a particular trade as an aspect of construction that can be modelled with NNs. Portas and AbouRizk [25] used an NN for predicting labour productivity for construction productivity for concrete formwork elements. The results indicate that a three-layered network with a fuzzy output structure performs the best for predicting the labour productivity for concrete formwork. Sonmez and Rowings [26] applied NN to estimate productivity for concrete construction activities. Lu, AbouRizk, and Hermann [27] employed the probability inference neural network (PINN) and MLPNN to predict construction labour productivity based on real historical data. Abou Rizk, Knowles, and Hermann [28] employed a two-stage NN to estimate labour productivity rates. They concluded that an adequate historical record and understanding input factors are the most important factors in productivity prediction. Fayek and Oduba [29] applied a fuzzy expert system for predicting construction labour productivity. Ezeldin and Sharara [30] employed NNs for the prediction of the labour productivity rates of concrete construction activities, incorporating both quantitative and qualitative factors. It was concluded that the NNS has reasonable generalisation competences. Using historical data, Song and AbouRizk [4] predicted construction productivity with ANN and discrete-event simulation techniques. Oral and Oral [31] investigated the relationship between several factors and crew productivity using NNs and regression methods. Muqeem, Khamidi, Idrus, and Bin Zakaria [32] employed NN for the prediction of production rate for the installation of beam formwork. Moselhi and Khan [33] employed stepwise variable selection, fuzzy, and NN for ranking parameters affecting construction labour productivity. Heravi and Eslamdoost [34] employed NNs for estimation the rates of construction labour productivity. El-Gohary, Aziz, and Abdel-Khalek [35] introduced and examined NN for prediction and controlling construction labour productivity. Golnaraghi, Zangenehmadar, Moselhi, and Alkass [36] compared various NN techniques including ANFIS, GRNN, BNN, and the radial basis function neural network (RBFNN) for predicting productivity. The BPNN method was found to be the superior one,

3. RESEARCH METHOD

In this investigation, the SVM, MART, MLPNN, and GRNN methods were employed for the prediction of the labour productivity rates of concrete construction activities. This research was conducted in four major stages: (1) data identification and acquisition, (2) model development, (3) model validation, and (4) model evaluation.

4. DATA IDENTIFICATION AND ACQUISITION

4.1 Questionnaire Design

The recognizable proof and assessment of factors that impact labour productivity rates of concrete construction activities are required to create the models. Numerous studies were conducted to define and describe factors affecting labour productivity. These were used to develop the questionnaire form, which involves factors affecting the labour productivity rates of concrete construction activities [37,30]. Table 1 shows the influencing factors for concrete works [30].

4.2 Pilot Study

A pilot study was conducted to ensure the clarity and relevance of the initial questionnaire to participants and to validate and improve the questionnaire in terms of the wording of statements, overall content, and organize and format. Three researchers in the same area had the questionnaire provided. Amendments were created, based on their input. After that, in personal interviews with five seasoned project managers, each of whom had at least 15 years of experience with residential, commercial and industrial projects, the updated questionnaire was addressed. This stage was performed in arrange to adapt the variables contained in the literature to the local market.

4.3 Measuring Factors and Related Labour Productivity

Construction productivity can be measured in a variety of ways depending on the particular field of construction being studied. The ratio of output to work hours (production rate) and the ratio of work hours to output (inverse of the production rate) are widely used for measuring labour productivity. The inverse of the production rate was used as the indicator of productivity in this study; thus, calculations such as worker days per unit would be produced [37,30]. These calculations were utilized because the worker hour is included as data. The production rates were estimated according to:

$$FP(worker\ days/m^3) = \frac{FCS(workers) \times t_{F(days)}}{CQ(m^3)} \tag{1}$$

$$SFP(worker\ days/t_s) = \frac{SCS(workers) \times t_{S(days)}}{SQ(m^3)} \tag{2}$$

$$CPP(worker\ days/m^3) = \frac{PCS(workers) \times t_{C(days)}}{CQ(m^3)} \tag{3}$$

Where:

FP: Formwork productivity,
SFP: Steel fixing productivity,
CPP: Concrete pouring and finishing productivity,
FCS: Formwork crew size,
SCS: Steel crew size,
PCS: Pouring crew size,
t_F: Formwork assembly duration,
t_S: Steel fixing duration,
t_C: Concrete pouring duration,
CQ: Concrete quantity, and
SQ: Steel quantity.

4.4 Data Collection

After an adjustment of the questionnaire structure based on the pilot study, there were 276 interviews were conducted on 12 different projects. The participants were design or site engineers with over 10 years of local market experience with concrete building activities. The twelve projects chosen for the study were commercial, industrial, and residential. Accordingly, the chosen concrete elements were plain concrete foundations, isolated reinforced concrete footings, rafts, columns, slabs, beams, and shear walls.

5. CONSTRUCTION LABOUR PRODUCTIVITY PREDICTION METHODS

5.1 Support Vector Machine (SVM)

The concept in regressive SVM is to map a low-dimensionality input space x to a higher dimensionality feature space F through a non-linear mapping “ $\boldsymbol{\phi}$” space, and to make linear regressions in this function space using the following [38]:

$$f(x) = w.\phi(x) + b \tag{4}$$

Where:

$\boldsymbol{\phi}(\boldsymbol{x})$: the high-dimensionality feature space non-linearly mapped from the input space,
b: the term of bias, and
w: the weight vector.

In this paper, the radial basis function (RBF) is employed, defined as $K(x_i, x) = e^{(-\|x_i - x\|^2/2\delta^2)}$, where δ^2 is the kernel parameter of the RBF kernel. The performance of SVM generalisation depends on the good choice of meta-parameters (C and ε) and kernel function parameter (δ^2) [38]. Therefore, these parameters must be chosen carefully. In this study, the parameters of SVM were selected using a genetic algorithm (GA).

Table 1 Factors affecting labour productivity for concrete works [32]

Factor	*FP*	*SFP*	*CPP*
Structural element (*SE*)	√	√	√
Concrete quantity (*CQ*)	√	-	√
Steel quantity (*SQ*)	-	√	
Crew size (*CS*)	√	√	√
Falsework type (*FAT*)	√	-	-
Formwork type (*FOT*)	√	-	-
Pouring method (*PM*)	-	-	√
Supervision (*S*)	√	√	√
Labour skills (*LS*)	√	√	√
Overtime (*O*)	√	√	√
Task complexity (*TO*)	√	√	√
Material accessibility (*MA*)	√	√	√
Degree of repetition (*DR*)	√	√	√
Temperature conditions (*TC*)	√	√	√

5.2 Multiple Additive Regression Trees (MART)

The MART approach [39] belongs to the family of modelling approaches for boosted-regression-tree, which are extended by a strong learning method called boosting [40]. A model of regression tree divides the *x* space into several separate regions and estimates a constant value for *y* in each region. Boosting approaches are usually used to substantially improve the overall performance of a given estimation technique with the aid of iteratively producing instances of the approach from a training data set, giving more weight to poorly predicted results, and incorporating them in a forward 'stage-wise' procedure. For regression trees, MART uses a specific type of stochastic gradient boosting [39].

5.3 Multilayer Perceptron Neural Network (MLPNN)

MLPNN can be multi-layered. The MLPNN architecture has an input layer, an output layer, and at least one hidden layer, all of them are completely interconnected. The network is exposed to a series of training data, and errors are determined based on the resulting outputs. The weights and biases are modified by these errors, which eventually leads to optimal and bias values which can imitate the model.

The network's performance can be influenced by a variety of parameters, such as the number of layers and neurons of each layer, initial conditions, momentum factor, and learning factor. In this study, a GA was utilised to adjust the MLPNN model up to optimization of its efficiency.

5.4 General Regression Neural Network (GRNN)

GRNN is an approach first proposed by Specht [41] as a variation on RBFNN. It is an effective NN that can provide a sound solution for any approximation problem. It belongs to the family of feed-forward NNs, which use a non-linear-regression learning mechanism [42]. The learning process is similar to creating a multidimensional surface in the space that provides the statistically optimal approximation for the data set. With GRNN, if the training set is large, the prediction error approaches zero. A Gaussian kernel function is used; its sigma value (σ) determines the spread of the function.

5.5 Validation Procedure

For each method (SVM, MART, MLPNN, and GRNN), the observed and predicted values of the construction labour productivity of formwork assembly, steel fixing, and concrete pouring and finishing were compared using several complementary indices: the root mean square error (*RMSE*), the normalised mean square error (*NMSE*), the mean absolute error (*MAE*), the correlation coefficient (*R*), and the mean squared error (*MSE*),. These five criteria are defined as follows [43]:

$$NMSE = \frac{1}{N}\sum_{i=1}^{N}\frac{(P_i - O_i)^2}{\bar{P}\bar{O}} \tag{6}$$

$$R = \frac{\sum_{i=1}^{N}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{N}(P_i - \bar{P})^2 \sum_{i=1}^{N}(O_i - \bar{O})^2}} \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \tag{8}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2 \tag{9}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i| \tag{10}$$

where O_i is an observed value, P_i is the corresponding predicted value, N is the total number of data points under validation, $\bar{O}$ is the mean value of the observations, and $\bar{P}$ is the mean value of the predictions.

6. DESIGN OF SOFT COMPUTING MODELS

6.1 SVM

The data were used to develop the SVM-based model after identifying the factors had a significant impact on labour productivity for concrete. To order to develop an effective model, it is important to choose carefully in advance optimal values of the essential parameters (C, ε, and δ^2) of the SVM. The values of the selected parameters for the various SVM models are displayed in Table 2.

The models for the prediction of labour productivity of concrete construction works were developed using the training data and tested using the validation data. Table 3 shows the error statistics for the observed and predicted labour productivity of concrete construction works under all four methods. The *NMSE, MSE, MAE, RMSE*, and *R* values for the SVM prediction model for the labour productivity of formwork assembly were 0.1445, 0.1556, 0.2496, 0.3945, and 0.938, respectively. For steel fixing, the values were 0.1481, 2.8947, 1.2928, 1.7013, and 0.9317, respectively. For concrete pouring and finishing, the values were 0.0324, 0.6881, 0.2892, 0.8295, and 0.9838, respectively.

Table 2 Parameter values selected for the SVM labour productivity models

Concrete work	Free parameters		
	C	ε	δ^2
FP	12.831	0.0015	29.62
SFP	13.932	0.0017	31.43
CPP	21.436	0.0012	38.45

During the prediction of the labour productivity for concrete pouring and finishing, the SVM models approximate well the data pattern. The *R* values vary from 0.9317 to 0.9838.

Table 3 Error statistics for labour productivity for concrete construction works as predicted by the four models.

	FP				*SFP*				*CPP*			
Metric	MLPNN	GRNN	SVM	MART	MLPNN	GRNN	SVM	MART	MLPNN	GRNN	SVM	MART
NMSE	0.8768	0.2882	0.1445	0.0791	0.8745	0.0975	0.1481	0.2426	0.6185	0.0005	0.0324	0.4134
MSE	1.0386	0.3414	0.1556	0.0937	17.0924	1.9067	2.8947	4.4905	13.1037	0.0113	0.6881	0.8651
MAE	0.6916	0.3305	0.2496	0.1465	3.1327	0.6217	1.2928	1.4127	0.8813	0.0516	0.2892	0.25062
RMSE	1.0191	0.5843	0.3945	0.3061	4.1342	1.3808	1.7013	2.119	3.6199	0.1061	0.8295	0.93016
R	0.3533	0.8486	0.938	0.9596	0.3571	0.951	0.9317	0.8969	0.7958	0.9997	0.9838	0.8266

6.2 MLPNN

Another prediction model that was developed is the MLPNN model. Integrated performance validation showed that the number of hidden layers was one and the number of neurons in the hidden layer was seven, ten, and six for the prediction of the labour productivity for formwork assembly, steel fixing, and concrete pouring and finishing, respectively. When the MLPNN model was applied to the labour productivity of formwork assembly, the *NMSE*, *MSE*, *MAE*, *RMSE*, and *R* values were 0.8768, 1.0386, 0.6916, 1.0191, and 0.3533, respectively. For steel fixing, the values were 0.8745, 17.0924, 3.1327, 4.1342, and 0.3571, respectively. For concrete pouring and finishing, the values were 0.6185, 13.1037, 0.8813, 3.6199, and 0.7958, respectively. A review of the models' results reveals that the performance of MLPNN was the poorest. Table 3 shows the lower *R* values, which vary from 0.3533 to 0.7958 for the different MLPNN models.

6.3 GRNN

The prediction of labour productivity for concrete construction works was repeated using the GRNN method. The optimal σ values are shown in Table 4. For formwork assembly, the *NMSE*, *MSE*, *MAE*, *RMSE*, and *R* values obtained were 0.2882, 0.3414, 0.3305, 0.5843, and 0.8486, respectively. For steel fixing, the values obtained were 0.0975, 1.9067, 0.6217, 1.3808, and 0.951, respectively, and for concrete pouring and finishing, values of 0.0005, 0.0113, 0.0516, 0.1061, and 0.9997, respectively, were obtained. For steel fixing works and concrete pouring and finishing, the results show that using the GRNN models significantly reduced the overall error and that it was able to accurately estimate the labour productivity. Also, the GRNN models approximate well the data pattern. From Table 3, it is seen that the *R* values vary from 0.8486 to 0.9997.

6.4 MART

When the MART model was applied to predict the labour productivity for formwork assembly, the values for *NMSE*, *MSE*, *MAE*, *RMSE*, and *R* were 0.0791, 0.0937, 0.1465, 0.3061, and 0.9596, respectively. The MART model approximates well the data pattern. For steel fixing, the values were 0.2426, 4.4905, 1.4127, 2.119, and 0.8969, respectively. For concrete pouring and finishing, the values were 0.4134, 0.8651, 0.25062, 0.93016, and 0.8266, respectively. From Table 3, it is seen that the *R* values vary from 0.8226 to 0.9596.

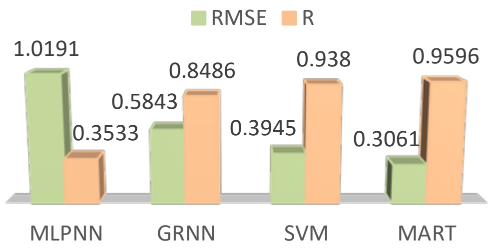
Table 4 Optimal σ values for the GRNN models

Variable	Optimal σ		
	FP	*SFP*	*CPP*
SE	1.028	0.343	0.972
CQ	0.714	-	1.125
SQ	-	0.1632	-
CS	1.293	0.655	0.429
FAT	4.652	-	-
FOT	3.770	-	-
PM	-	-	0.151
S	1.81	0.793	0.233
LS	0.0001	0.565	0.595
O	0.0001	0.224	0.0001
TC	0.766	0.483	0.263
MA	2.931	1.030	0.613
DR	0.456	0.461	0.001
TC	1.978	0.473	0.0001

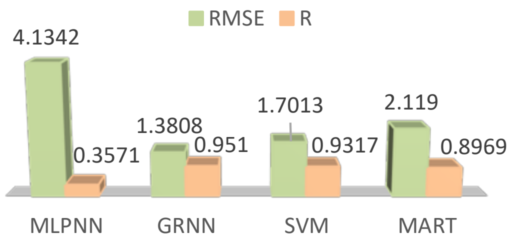
6.5 Comparison of Soft Computing Methods

According to the measures (*NMSE*, *MSE*, *MAE*, *RMSE*, and *R*), the GRNN models performed the best for predicting the labour productivity for steel fixing and concrete pouring and finishing. For formwork assembly, the MART prediction model was the superior one. The performance of MLPNN was the poorest, as indicated by the statistical analyses. It also obtained lower *R* values, which varied from 0.3533 to 0.7958 for the MLPNN models.

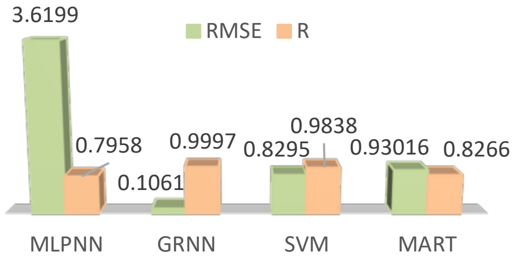
The results show that use of the MART model significantly reduces overall errors in predictions of labour productivity for formwork assembly. The *RMSE* of the MART model was an improvement of 232.93%, 90.89%, and 28.88% over the MLPNN, GRNN, and SVM models, respectively (Fig.1a). The MART model approximates well the data pattern (*R* = 0.956). Fig.2a shows a comparison of the correlation coefficients for the four methods. In their research, Golnaraghi, Zangenehmadar, Moselhi, and Alkass [36] obtained *R* = 0.911 for the superior model for predicting formwork assembly productivity; therefore, the correlation between the collected formwork assembly productivity values and the predicted values obtained from the MART model used in this study (*R* = 0.9596) was judged to be good. Sonmez and Rowings [26] found *MSE* values that varied from 20.32 to 31.96, but the *MSE* value for the MART model used in this investigation was 0.0937. Thus, the MART model performs better for predicting formwork assembly productivity.



(a)



(b)



(c)

Fig.1 Comparison of *RMSE* and *R* for the four soft computing techniques. (a) Formwork assembly, (b) steel fixing, and (c) concrete pouring and finishing.

The *RMSE* of the GRNN model was an improvement of 199.41%, 23.21%, and 53.46% over MLPNN, SVM, and MART, respectively, for the labour productivity of steel fixing (Fig.1b), and 3,311.78%, 681.81%, and 776.68%, respectively, for that of concrete pouring and finishing (Fig.1c). Sonmez and Rowings [26] obtained *MSE* values varying from 3.97 to 4.27 and from 16.796 to 28.350 for concrete pouring models and concrete finishing models, respectively, but the *MSE* for the GRNN model used in this investigation for concrete pouring and finishing was 0.0113. Thus, the GRNN model performs better for predicting labour productivity for concrete pouring and finishing. The GRNN models approximate well the data pattern for formwork assembly and concrete pouring and finishing (*R* = 0.951 and 0.9997, respectively); see Fig.1a and c.

7. CONCLUSION

Construction labour productivity is a basic piece of information needed to estimate, budget, and schedule a construction project. This investigation aimed to demonstrate a way to use soft computing techniques (SVM, MLPNN, GRNN, and MART) to predict the productivity rates of concrete construction activities. The results indicate that the GRNN models perform the best for predicting labour productivity for steel fixing and concrete pouring and finishing. However, MART is the most successful method for predicting labour productivity for formwork assembly. MLPNN is the poorest at predicting labour productivity for all three concrete construction activities. The four techniques slightly over-predicted the labour productivity of concrete construction activities.

This investigation shows that the GRNN and MART methods can be useful as supervised learning-based tools for predicting labour productivity for steel fixing and concrete pouring and finishing and for formwork assembly, respectively.

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