Predicting Maintenance Labor Productivity in Electricity Industry using Machine Learning: A Case Study and Evaluation

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***Abstract*—Predicting maintenance labor productivity is crucial for effective planning and decision-making in the electricity industry. This paper aims at predicting maintenance labor productivity using various machine learning methods, utilizing a real-world case study from the electricity industry. Additionally, the study evaluates the performance of the employed machine learning methods. To meet this objective, 1750 productivity measures have been used to train (80%) and test (20%) prediction models using Artificial Neural Networks, Support Vector Machines, Random Forest, and Multiple Linear Regression methods. The models' performance was evaluated based on the mean squared error, mean absolute percentage error, and testing time. The results indicated that the Artificial Neural Networks model - specifically, a feedforward network with a backpropagation algorithm - outperformed the other models (Multiple Linear Regression, Support Vector Machines, Random Forest). These results highlight the effectiveness of machine learning, particularly the Artificial Neural Networks prediction model, as an invaluable tool for decision-makers in the electricity industry, aiding in more effective maintenance planning and potential productivity improvement.**

Keywords—Productivity; machine learning; maintenance; prediction; ANN

I. Introduction

The electricity industry plays a vital role in the modern world, underpinning a wide array of economic activities and societal functions. The demand for electricity has increased enormously worldwide, with an annual average of 2.6 percent from 2010 to 2021 [1]. As the demand for reliable and uninterrupted electric power supply grows, the efficient maintenance of networks has become increasingly crucial in the electricity industry [2]. One critical component of efficient maintenance is the productivity of the maintenance labor force. Maintenance labor productivity is a measure of the effective use of resources while performing maintenance activities, usually expressed as the ratio of output to input [3]. It can significantly impact the availability, efficiency, and reliability of electric power networks. High productivity can lead to reduced breakdowns, improved performance, lower operational costs, and the avoidance of expensive blackouts.

However, predicting maintenance labor productivity is a complex task. Numerous factors, such as type of equipment, labor skills and experience, supervisor competency, and even external factors like weather conditions, can influence productivity. Accurate prediction of productivity allows for effective planning, ultimately leading to better maintenance outcomes and improved service reliability. As it will be shown in the following section, and to the best of the authors' knowledge, no study was conducted into predicting maintenance labor productivity using machine learning methods, especially in the electricity industry.

This complexity, alongside the pivotal role of productivity in the electricity industry, motivates the central research question of this study; how effective are machine learning models at predicting maintenance labor productivity? To address this question, the objectives of this study are to develop a various machine learning models, including artificial neural networks (ANN), support vector machines (SVM), random forests (RF), and multiple linear regression (MLR) to predict maintenance labor productivity with a focus on electricity industry and to evaluate the performance of these machine learning models. For this purpose, the study will use a combination of qualitative and quantitative research methods, employing a real-world case study.

The structure of this paper is organized as follows: Section II provides insight into productivity and reviews the research on the application of machine learning in predicting labor productivity, while Section III describes the research methodology used in this study. Section IV focuses on the data collection, and data preprocessing. Section V illustrates the models development. The results are presented and discussed in Section VI. Finally, in Section VII the study has been concluded.

II. Literature Review

A. Labor Productivity Measurement and Influencing Factors

Productivity serves as the ultimate engine of growth in the global economy. Various methods for measuring productivity are presented in the literature. The most prevalent method measures productivity as a ratio of work accomplished or units produced per man-hour [4] [5]. The inverse is also commonly used, which measures productivity as a ratio of man-hours per work accomplished or unit produced [6].

Another method measures productivity as the ratio of earned hours to actual hours [7] [8] [9] [10]. The concept "earned hours" is popular in the United States of America (USA), refers to establish a base or a norm for each activity.

According to the American Association of Cost Engineers, a norm is defined as the number of man-hours required to complete a defined activity under a specific set of stated conditions or qualifications [11]. Thus, a number of earned hours is associated with a norm and each unit of work accomplished.

Extensive literature has attempted to investigate and identify the factors influencing labor productivity across various industries. The most influential factors include labor skills and experience [12] [13] [14] [15] [16] [17] [18] [19] [20] [21] [22] [23] [24], labor motivation [25], supervisor competency [12] [16], and weather conditions such as temperature and humidity [15] [26].

B. *Application of Machine Learning in Prediction of Labor Productivity*

Machine learning, a subset of artificial intelligence, provides machines with the ability to learn and improve from experience. Moreover, it has the capability to handle large volumes of data, learn from this data, and make accurate predictions or decisions without being explicitly programmed. The application of machine learning to predict labor productivity is an emerging area of research that has demonstrated promising results across various industrial sectors.

The earliest study found describing a real application of machine learning to predict labor productivity proposed an ANN model for predicting labor productivity in concrete formwork activity [27]. Subsequent studies used ANN to predict labor productivity for concrete pouring, formwork and concrete finishing, and pipe installation, respectively [28] [29]. In 2006, a study proposed a framework to predict the labor productivity rates of forms assembly, steel fixing, and concrete pouring activities using ANNs [30]. Oral and Oral [31] developed ANN to predict crew productivity for ready mixed concrete, formwork, and reinforcement activities. The authors indicated that ANNs have proved to make productivity predictions significantly better than statistical regression methods, which also agreed by other research works such as [32] [33].

Similarly, ANN was used by [34] to predict the required man-hours for the formwork activity of reinforced concrete framed building projects. The developed model produced results reasonably close to actual field measurements, which was also indicated by [35], who found that the developed ANN has the ability to predict the labor productivity of marble finishing works for floors with a 90.9 percent of accuracy. Furthermore, Heravi and Eslamdoost [36] utilized ANN to predict labor productivity in the concrete foundations work of gas, steam, and combined cycle power plant construction projects. The study illustrated a structured method for developing the ANN model of labor productivity as well as the training process of neural network. Moreover, a study conducted by [37] applied ANN to predict construction labor productivity. The results showed that the ANN adequately converged and have noticeable and reasonable generalizing capabilities, which also is consistent with [30].

A study by [38] applied various ANNs to predict labor productivity norms for the formwork activity of two high-rise buildings. Moreover, a comparison of each ANN model's performance was conducted to identify the best model. The collected data set was utilized in the research work of [39], where the authors proposed a novel approach for predicting labor productivity using ANN. The developed network showed a good performance from the point of view of generalization.

Mlybari [40] did an investigation aimed to demonstrate the use of various machine learning techniques to predict the labor productivity rates of concrete construction activities, including formwork, steel fixing, and concrete pouring and finishing. The result showed that the developed ANN outperformed the other techniques such as SVM and could be useful to predict labor productivity. Another study found that the performance of RF model yielded better results in predicting labor productivity compared to the ANN model [41]. Conversely, the study by [23] suggested that the performance of SVM is better compared to RF in predicting construction labor. Another study used machine learning–based approach to analyze and predict construction task productivity [42].

Despite these applications and to the best of the authors' knowledge, no previous research has applied machine learning to predict maintenance labor productivity in the electricity industry. Hence, this study fills this gap in the literature by applying and evaluating different machine learning models, including ANN, SVM, RF, and MLR, for the prediction of maintenance labor productivity in the electricity industry.

III. Research Method

The primary purpose of this study is to explore the application of machine learning in prediction maintenance labor productivity with a focus on electricity industry. Fig. 1 illustrates the flowchart of the research methodology. The initial step involves the identification of inputs and outputs for the machine learning models. The selection of model inputs will be based on a literature review and expert opinion, while the model output is defined as the percentage of labor productivity, as shown in (1) [10].

$$\text{Productivity (\%)} = (\text{Earned hours} / \text{Actual hours}) \times 100 \qquad (1)$$

Following the identification of the appropriate inputs and output for the machine learning models, the next step is data acquisition. The data will be collected from the selected company. This collected data will then be preprocessed as needed through several steps, which include data cleaning, data encoding, and data normalization. Subsequently, the preprocessed data will be randomly partitioned into training and testing sets.

The MATLAB 2023a software will be utilized for the development, training and testing of the four machine learning models, specifically ANN, SVM, RF, and MLR. Each model's performance will be evaluated using a set of defined criteria, including the Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and the computational time required for testing. MSE and MAPE will be calculated using (2) and (3), respectively [43]. Ultimately, the model that exhibits the best performance, in accordance with the evaluation criteria, will be selected. This model will form the basis of the predictive tool that this research aims to develop.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{i\ actual} - Y_{i\ predict}\right)^2 \qquad (2)$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left(\frac{\left|Y_{i\,actual} - Y_{i\,predict}\right|}{Y_{i\,actual}}\right) \qquad (3)$$

Where 'n' represents the number of data points in the dataset used for prediction, '$Y_{i\,actual}$' denotes the actual productivity value of the ith instance in the dataset, and '$Y_{i\,predict}$'refers to the predicted productivity value ith instance in the dataset.

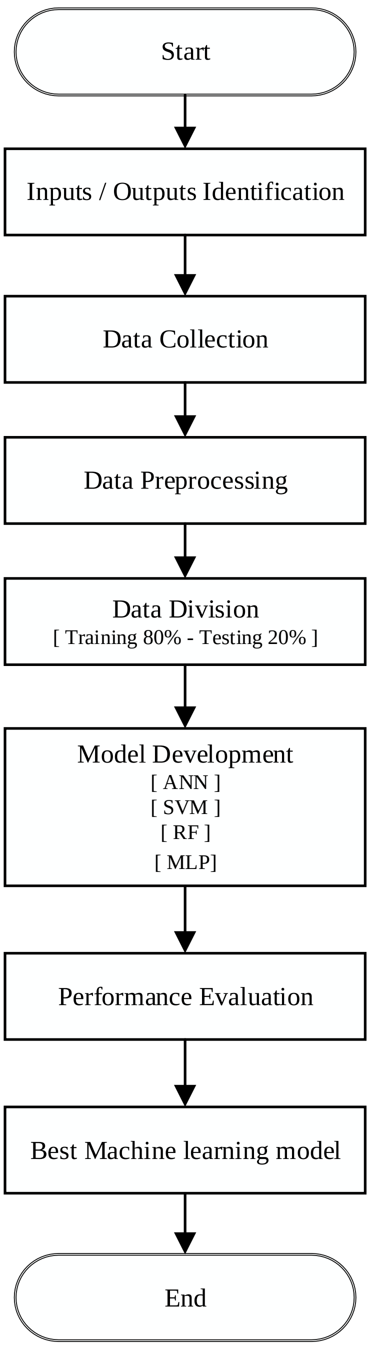

Fig. 1. Research method flowchart.

IV. Data Collection and Preprocessing

A. Data Collection

The dataset utilized in this research was obtained from a large electricity company that is responsible for supplying power. A comprehensive set of data was collected, incorporating all the influencing factors identified from the literature review and expert opinion. The dataset contains records of conducted preventative maintenance tasks for substations and includes inputs variables such as type of equipment, level of labor skill, labor health condition, level of safety measures, labor experience, level of labor motivation or commitment, level of supervisor competency. Because the main dataset did not include all the identified factors, additional data such as temperature and humidity were obtained from the National Center of Meteorology and synchronized with the date and time of the task.

The output parameter, percentage of labor productivity, was calculated by dividing the earned hours by the actual hours. The data collected spans a period of twelve months, offering a substantial volume of information for the models to learn from and making the prediction robust and applicable across different periods.

B. Data Preprocessing

Data preprocessing is a crucial phase in addressing a real-world problem using machine learning and plays a significant role in obtaining promising results. This phase involves several steps:

1) Data cleansing or cleaning: This process identifies and corrects, or removes, inaccuracies, discrepancies, and inconsistencies within datasets. A comprehensive data cleaning was implemented. Certain records within the dataset were excluded due to their lack of labor-related information or because they were duplicates. Furthermore, the units of measure for both earned and actual time were standardized to exclusively use minutes. This uniformity helps to prevent potential discrepancies or misunderstandings that could arise from inconsistent units.

2) Data encoding: This involves transforming categorical variables into a numeric format. The label encoding technique was employed to encode categorical data into numerical values as machine learning can only process numerical data. Table I provides an overview of the data description, while Table II summarizes the descriptive statistics of the collected data.

3) Data partitioning: The total available data is 1750 instances that randomly divided into two sets following an 80:20 ratio; 80% for training (1400 instances) and 20% for testing (350 instances). The training dataset will be used to train the model, and the testing dataset will assess the model's performance on unseen data.

4) Data normalization: This step is necessary and essential to enhance the performance of machine learning [44]. Min-max normalization, one of the most commonly employed methods, was utilized in this study to normalize data within the range of 0 to 1.

TABLE I. DATA DESCRIPTION

No.	Input Variables	Descriptions	Type	Value
1	Type of equipment	The type of equipment in which the task will be performed with.	Categorical	1: Aspiration Smoke Detection
				2: Fire Alarm System
				3: Fire Fighting System
				4: Gas Extinguishing System
				5: Gas Insulated Switchgear
				6: Transformer
				7: Water Mist System
2	Skill level	The technical skill level of labor who perform the task.	Categorical	1: Novice
				2: Intermediate
				3: Competent
				4: Proficient
3	Health condition	The overall health condition of labor who perform the task.	Categorical	1: Poor
				2: Fair
				3: Good
				4: Excellent
4	Safety measures	The level of safety measures the labor required to be taken while perform the task.	Categorical	1: Basic
				2: Moderate
				3: High-Level
				4: Extreme
5	Temperature	The average temperature of a day that the task perform in.	Numerical	Celsius degree (°C)
6	Labor experience	Number of years of experience the labor have.	Numerical	Years
7	Level of supervisor competency	The competency level of supervisor.	Categorical	1: Novice
				2: Intermediate
				3: Competent
				4: Proficient
8	Level of labor motivation or commitment	The level of labor motivation or commitment who perform the task.	Categorical	1: Disengaged
				2: Low
				3: Medium
				4: High
9	Humidity	The average humidity of a day that the task perform in.	Numerical	Percentage
No.	**Output Parameter**	**Descriptions**	**Type**	**Value**
1	Labor Productivity	The actual labor productivity value, calculated by dividing earned hours and actual hours.	Numerical	Percentage

TABLE II. DESCRIPTIVE STATISTICS OF THE COLLECTED DATA

Variable	Mean	SE Mean	Std. Dev	Min	Median	Max
Type of equipment	4.85	0.04	1.50	1	5	7
Skill level	3.60	0.01	0.50	2	4	4
Health condition	3.68	0.01	0.57	2	4	4
Safety measures	3.05	0.02	0.81	2	3	4
Temperature	29.62	0.15	6.30	18.9	29.9	40.1
Labor experience	12.46	0.13	5.27	3	12	28
Level of supervisor competency	3.21	0.02	0.64	2	3	4
Level of motivation or commitment	3.69	0.01	0.54	2	4	4
Humidity	0.45	0.00	0.20	0.10	0.44	1
Labor productivity	1.01	0.00	0.17	0.69	1.01	1.44

V. Machine Learning Models Development

A. Artificial Neural Networks

One of the main methods in machine learning is ANNs. Moreover, it is an information processing paradigm biologically inspired and designed to simulate the way in which the human brain processes information [45]. ANN can be defined as structures comprised of densely interconnected adaptive simple processing elements called artificial neurons or nodes that are capable of performing massively parallel computations for data processing and knowledge representation [46] [47] [48]. The ANN is developed and derived to have a function similar to the human brain by memorizing and learning various tasks and behaving accordingly [49]. Once ANN is trained, it is able to recognize similarities when presented with a new input pattern, resulting in a predicted output pattern. ANNs are now recognized worldwide as the most effective and appropriate machine learning method for prediction [50].

In this study, an ANN model was used for predicting labor productivity. The configuration of the ANN model consisted of one input layer, one hidden layer, and one output layer. The input layer contained nine neurons, equivalent to the number of input variables. The hidden layer, consisting of 15 neurons, employed a sigmoid activation function (logsig), while the output layer used a linear activation function (purelin). The model was trained using the backpropagation algorithm, which is the most common learning algorithm in neural networks. The structure of ANN model is illustrated in Fig. 2.

B. Support Vector Machines

SVM is a supervised machine learning method, often used in classification problems but also capable of performing regression. SVM operate by mapping input data into a high-dimensional feature space, and then finding an optimal hyperplane that maximizes the margin between different classes in the feature space, hence making it a suitable choice for a range of predictive modeling problems. In this study, an SVM model was developed for predicting labor productivity.

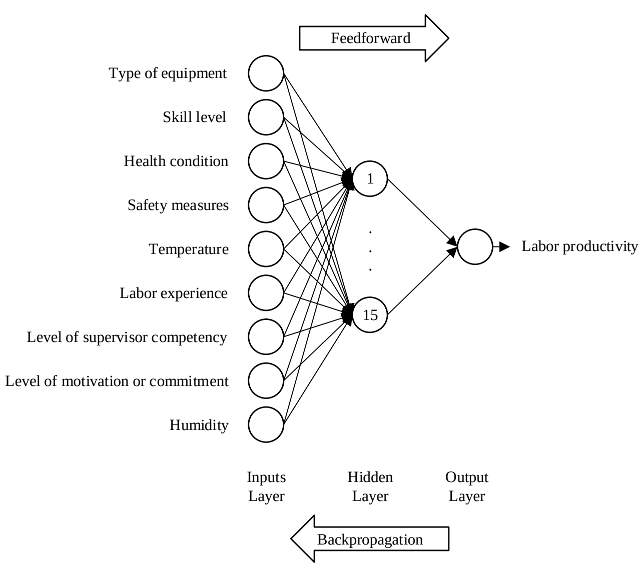

Fig. 2. The structure of ANN.

C. Random Forests

RF is a robust and effective machine learning methods for prediction because of their good performance, scalability, and ease of use [51]. It operates as an ensemble learning method by constructing a multitude of decision trees and producing an output that is the average prediction of the individual trees. Given its ability to mitigate overfitting while maintaining high precision, RF has found extensive application in various predictive modeling tasks. In this study, an RF model was employed to predict labor productivity. The model was configured with 200 decision trees, a parameter that was chosen to balance between the model's complexity and its ability to learn the underlying patterns in the data.

D. Multiple Linear Regression

MLR is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of MLR is to model the relationship between the explanatory and response variables. The development and application of MLR in this study offers a traditional statistical approach to the problem of predicting labor productivity, providing a contrast and a basis for comparison with the more sophisticated machine learning models.

VI. Results and Discussion

From the results presented in Table III, it is evident that the ANN exhibits the best overall performance in terms of a balance between low error rates and efficient testing times.

TABLE III. Performance Comparison between ANN, SVM, RF, and MLR Models

Model	MSE	MAPE	Testing Time (Second)
ANN	0.0250	12.494	0.012969
SVM	0.0595	19.825	67.1444
RF	0.0330	12.027	1.1359
MLR	0.0286	14.136	0.041887

In assessing prediction performance, measured by MSE, the ANN model outperforms the SVM, RF, and MLR models with an MSE of 0.0250. The MLR follows closely with an MSE of 0.0286, and RF comes in third with an MSE of 0.0330. The SVM model shows the least performance with the highest MSE of 0.0595.

However, in terms of MAPE, the RF model excels with the lowest MAPE of 12.027. The ANN model trails closely behind with a MAPE of 12.494. However, MLR and SVM models show higher MAPEs of 14.136 and 19.825, respectively, indicating a greater margin of error in their predictions. When considering the testing time, the ANN model outperforms the rest, requiring only 0.012969 seconds. The MLR model is slightly slower with a testing time of 0.041887 seconds, while RF takes notably longer at 1.1359 seconds. The SVM model, on the other hand, requires the most extended testing duration of 67.1444 seconds.

These results accentuate that the ANN model outperform the traditional statistical method in predicting labor productivity, aligning with the findings from studies [32], [37], and [38]. Furthermore, these results corroborate the conclusion of study [40] that set the ANN model as superior to the SVM model in labor productivity prediction. On the other hand, these findings conflict with another study [41], where the RF model demonstrated better results in predicting labor productivity compared to the ANN model. Further, the current study's results deviate from those of study [23], which found that the SVM model outperformed the RF model in labor productivity prediction. It's important to note that the performance evaluation in study [41] was based on the Mean Absolute Error and Root Mean Square Error metrics, while study [23] employed Percentage of Correct, Heidke Skill Score, Probability of Detection, False Alarm Ratio, and Peirce Skill Score metrics, respectively. Despite the limited number of studies comparing the performance of machine learning methods in predicting labor productivity, these results underscore the effectiveness of machine learning, and specifically, the ANN model, in labor productivity prediction.

VII. Conclusion

This study aimed to investigate the application of various machine learning techniques to predict labor productivity in the electricity industry. Four popular machine learning models, namely ANN, SVM, RF, and MLR, were developed and evaluated. The performance of the models was evaluated based on the MSE, MAPE, and testing time.

The results indicated that the ANN model performed the best overall, showcasing a balanced performance between low error rates and efficient testing times. This finding provides a clear answer to the study research question, showing that machine learning models, particularly ANNs, can effectively predict maintenance labor productivity in the electricity industry. However, it is important to note the limitations of this study. While the ANN model showed promising results, the findings may not be generalizable to all sectors due to the unique characteristics and variables of the electricity industry. Furthermore, the models developed in this study could serve as valuable tools for managers and decision-makers in the industry, allowing them to make informed decisions about labor management based on accurate productivity predictions. This contribution is significant as it provides a practical application of machine learning techniques in a real-world industry setting.

Future research should consider applying these models in other sectors and exploring other machine learning techniques for labor productivity prediction. There are still unanswered questions regarding the optimal machine learning techniques for different sectors, and how these models can be improved to increase their predictive accuracy and efficiency. Additionally, future research should also aim to address the limitations of this study, such as the potential lack of generalizability, by conducting similar studies in various industry settings.

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References

[1] IEA, "World Energy Outlook 2022," IEA, Paris, 2022.

[2] A. Froger, M. Gendreau, J. E. Mendoza, É. Pinson and L.-M. Rousseau, "Maintenance scheduling in the electricity industry: A literature review," European Journal of Operational Research, vol. 251, no. 3, pp. 695-706, 2016.

[3] W. J. Stevenson, Operations Management: Theory and Practice, New York: McGraw-Hill Education, 2012.

[4] G. P. Cosmetatos and S. Eilon, "Effects of productivity definition and measurement on performance evaluation," European Journal of Operational Research, vol. 14, no. 1, pp. 31-35, 1983.

[5] D. W. Halligan, L. A. Demsetz, J. D. Brown and C. B. Pace, "Action-Response Model and Loss of Productivity in Construction," Journal of Construction Engineering and Management, vol. 120, no. 1, pp. 47-64, 1994.

[6] H. R. Thomas, S. R. Sanders and S. Bilal, "Comparison of Labor Productivity," Journal of Construction Engineering and Management, vol. 118, no. 4, pp. 635-650, 1992.

[7] R. C. Parsons, "Improving productivity through work measurement," Journal - American Water Works Association, vol. 73, no. 12, pp. 610-613, 1981.

[8] H. R. Thomas, J. M. Guevara and C. T. Gustenhoven, "Improving Productivity Estimates by Work Sampling," Journal of Construction Engineering and Management, vol. 110, no. 2, pp. 178-188, 1984.

[9] A. S. Hanna, C.-K. Chang, K. T. Sullivan and J. A. Lackney, "Impact of Shift Work on Labor Productivity for Labor Intensive Contractor," Journal of Construction Engineering and Management, vol. 134, no. 3, pp. 197-204, 2008.

[10] M. E. Shehata and K. M. El-Gohary, "Towards improving construction labor productivity and projects' performance," Alexandria Engineering Journal, vol. 50, no. 4, pp. 321-330, 2011.

[11] American Association of Cost Engineers, "International Recommended Practice 10S-90: Cost Engineering Terminology," AACE International, Morgantown, 2019.

[12] H. M. Alinaitwe, J. A. Mwakali and B. Hansson, "Factors affecting the productivity of building craftsmen - studies of Uganda," Journal of Civil Engineering and Management, vol. 13, no. 3, pp. 169-176, 2007.

[13] A. Enshassi, S. Mohamed, Z. Abu Mustafa and P. E. Mayer, "Factors affecting labour productivity in building projects in the Gaza strip," Journal of Civil Engineering and Management, vol. 13, no. 4, pp. 245-254, 2007.

[14] S. Islam and . S. T. Syed Shazali, "Determinants of manufacturing productivity: pilot study on labor-intensive industries," International Journal of Productivity and Performance Management, vol. 60, no. 6, pp. 567-582, 2011.

[15] A. M. Jarkas and C. G. Bitar, "Factors Affecting Construction Labor Productivity in Kuwait," Journal of Construction Engineering and Management, vol. 138, no. 7, pp. 811-820, 2012.

[16] K. M. El-Gohary and R. F. Aziz, "Factors Influencing Construction Labor Productivity in Egypt," Journal of Management in Engineering, vol. 30, no. 1, pp. 1-9, 2014.

[17] A. M. Jarkas, R. A. Al Balushi and P. K. Raveendranath, "Determinants of construction labour productivity in Oman," International Journal of Construction Management, vol. 15, no. 4, pp. 332-344, 2015.

[18] M. A. Hiyassat, M. A. Hiyari and G. J. Sweis, "Factors affecting construction labour productivity: a case study of Jordan," International Journal of Construction Management, vol. 16, no. 2, pp. 138-149, 2016.

[19] A. Azadeh, M. P. Ahvazi and S. M. Haghighi, "An intelligent algorithm for determination and optimization of productivity factors in upstream oil projects," Journal of Petroleum Science and Engineering, vol. 167, pp. 375-395, 2018.

[20] A. Hasan, B. Baroudi, A. Elmualim and R. Rameezdeen, "Factors affecting construction productivity: a 30 year systematic review," Engineering, Construction and Architectural Management, vol. 25, no. 7, pp. 916-937, 2018.

[21] W. Alaghbari, A. A. Al-Sakkaf and B. Sultan, "Factors affecting construction labour productivity in Yemen," International Journal of Construction Management, vol. 19, no. 1, pp. 79-91, 2019.

[22] P. Pornthepkasemsant and S. Charoenpornpattana, "Identification of factors affecting productivity in Thailand's construction industry and proposed maturity model for improvement of the productivity," Journal of Engineering, Design and Technology, vol. 17, no. 5, pp. 849-861, 2019.

[23] M. H. Momade, S. Shahid, M. R. bin Hainin, M. S. Nashwan and A. T. Umar, "Modelling labour productivity using SVM and RF: a comparative study on classifiers performance," International Journal of Construction Management, vol. 22, no. 10, pp. 1924-1934, 2022.

[24] F. Nasirzadeh, M. Rostamnezhad, D. G. Carmichael, A. Khosravi and B. Aisbett, "Labour productivity in Australian building construction projects: a roadmap for improvement," International Journal of Construction Management, vol. 22, no. 11, pp. 2079-2088, 2022.

[25] M. P. Jalal and S. Shoar, "A hybrid framework to model factors affecting construction labour productivity: Case study of Iran," Journal of Financial Management of Property and Construction, vol. 24, no. 3, pp. 630-654, 2019.

[26] A. Agrawal and S. Halder, "Identifying factors affecting construction labour productivity in India and measures to improve productivity," Asian Journal of Civil Engineering, pp. 569-579, 2020.

[27] J. Portas and S. AbouRizk, "Neural Network Model for Estimating Construction Productivity," Journal of Construction Engineering and Management, vol. 123, no. 4, pp. 399-410, 1997.

[28] R. Sonmez and J. E. Rowings, "Construction Labor Productivity Modeling with Neural Networks," Journal of Construction Engineering and Management, vol. 124, no. 6, pp. 498-504, 1998.

[29] M. Lu, S. M. AbouRizk and U. H. Hermann, "Estimating Labor Productivity Using Probability Inference Neural Network," Journal of Computing in Civil Engineering, vol. 14, no. 4, pp. 241-248, 2000.

[30] A. S. Ezeldin and L. M. Sharara, "Neural Networks for Estimating the Productivity of Concreting Activities," Journal of Construction Engineering and Management, vol. 132, no. 6, pp. 650-656, 2006.

[31] E. L. Oral and M. Oral, "Predicting construction crew productivity by using Self Organizing Maps," Automation in Construction, vol. 19, no. 6, p. 791–797, 2010.

[32] M. Oral, E. L. Oral and A. Aydın, "Supervised vs. unsupervised learning for construction crew productivity prediction," Automation in Construction, vol. 22, p. 271–276, 2012.

[33] E. L. Oral, M. Oral and M. Andaç, "Construction Crew Productivity Prediction: Application of Two Novel Methods," International Journal of Civil Engineering, vol. 14, no. 3, p. 181–186, 2016.

[34] S. U. Dikmen and M. Sonmez, "An artificial neural networks model for the estimation of formwork labour," Journal of Civil Engineering and Management, vol. 17, no. 3, pp. 340-347, 2011.

[35] F. M. AL-Zwainy, H. A. Rasheed and H. F. Ibraheem, "Development of the Construction Productivity Estimation Model using Artificial Neural Network for Finishing Works for Floors with Marble," ARPN Journal of Engineering and Applied Sciences, vol. 7, no. 6, pp. 714-722, 2012.

[36] G. Heravi and E. Eslamdoost, "Applying Artificial Neural Networks for Measuring and Predicting Construction-Labor Productivity," Journal of Construction Engineering and Management, vol. 141, no. 10, pp. 1-11, 2015.

[37] K. M. El-Gohary, R. F. Aziz and H. A. Abdel-Khalek, "Engineering Approach Using ANN to Improve and Predict Construction Labor Productivity under Different Influences," Journal of Construction Engineering and Management, vol. 143, no. 8, pp. 1-10, 2017.

[38] S. Golnaraghi, Z. Z. Zangenehmadar, O. Moselhi and S. Alkass, "Application of Artificial Neural Network(s) in Predicting Formwork Labour Productivity," Advances in Civil Engineering, pp. 1-11, 2019.

[39] S. Golnaraghi, O. Moselhi, S. Alkass and Z. Zangenehmadar, "Predicting construction labor productivity using lower upper decomposition radial base function neural network," Engineering Reports, vol. 2, no. 2, pp. 1-16, 2020.

[40] E. A. Mlybari, "Application Of Soft Computing Techniques To Predict Construction Labour Productivity In Saudi Arabia," International Journal of GEOMATE, vol. 19, no. 71, pp. 203-210, 2020.

[41] S. Ebrahimi, A. R. Fayek and V. Sumati, "Hybrid Artificial Intelligence HFS-RF-PSO Model for Construction Labor Productivity Prediction and Optimization," Algorithms, vol. 14, no. 7, p. 214, 2021.

[42] L. Florez-Perez, Z. Song and J. C. Cortissoz, "Using machine learning toanalyze and predict construction task productivity," Comput Aided Civ Inf, vol. 37, pp. 1602-1616, 2022.

[43] A. Sadatnya, N. Sadeghi, S. Sabzekar , M. Khanjani, A. N. Tak and H. Taghaddos, "Machine learning for construction crew productivity prediction using daily work reports," Automation in Construction, vol. 152, pp. 1-22, 2023.

[44] D. Kim, "Normalization methods for input and output vectors in backpropagation neural networks," International Journal of Computer Mathematics, vol. 71, no. 2, pp. 161-171, 1999.

[45] S. A. Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," Journal of Pharmaceutical and Biomedical Analysis, vol. 22, no. 5, p. 717–727, 2000.

[46] R. Hecht-Nielsen, Neurocomputing, Massachusetts: Addison-Wesley, 1990.

[47] R. J. Schalkoff, Artificial Neural Networks, New York: McGraw-Hill, 1997.

[48] I. A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application," Journal of Microbiological Methods, vol. 43, no. 1, p. 3–31, 2000.

[49] C. C. Aggarwal, Neural Networks and Deep Learning, Cham: Springer, 2018.

[50] M. Paliwal and U. A. Kumar, "Neural networks and statistical techniques: A review of applications," Expert Systems with Applications, vol. 36, no. 1, pp. 2-17, 2009.

[51] L. Breiman, "Random Forests," Machine Learning, vol. 45, p. 5–32, 2001.