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DEVELOPMENT OF A MACHINE LEARNING-BASED LABOUR PRODUCTIVITY PREDICTION TOOL TO PRACTICE LEAN CONSTRUCTION

Abhay Saini[1] and Albert Thomas[2]

ABSTRACT

The construction industry is a labour-intensive industry. This is one of the reasons why the industry has significant room to incorporate lean principles and reduce waste. Various lean tools can be implemented in construction projects, such as Kanban, JIT and 5S. However, these tools majorly focus on activities at an aggregate level and do not always incorporate sub-activities carried out within a small activity. The productivity of smaller activities (activities that typically span from minutes to hours) is essential to be assessed and controlled to increase the efficiency of overall activity. This paper aims to develop a labour productivity prediction tool based on machine learning principles and lean ideologies to improve the overall productivity of construction activities, considering the productivity of sub-activities. The developed framework is demonstrated by analyzing the productivity of reinforcement activity in a construction project. In the study, inventory wastes are minimized using the prediction from the developed quantitative labour productivity prediction model. An increase of 13.7% in overall productivity is achieved through the implementation of the developed framework.

KEYWORDS

Lean construction process, value stream mapping, machine learning, lean theory

INTRODUCTION

The construction industry is a labour-centric industry, and it may remain the same in the coming decades. The growth of the industry and the subsequent infrastructure growth depend heavily on completing projects on time and as per the planned cost (M. Hafez, 2014). 30%-50% of the total cost of construction projects is only spent on labour costs (Asadullah Tahir et al., 2015), and therefore achieving optimum labour productivity is crucial to prevent time and cost overruns. There are several approaches to predicting labour productivity in construction projects. These studies can be categorized into four, as given below.

1. The time-series analysis method involves historical data on productivity levels over time to identify trends and patterns that can be used to make predictions about future productivity. (Song and Abourizk, 2008)
2. Project benchmarking involves comparing the productivity of a particular project to those of similar projects and using this information to make predictions about future productivity. (Abdel-Razek et al., 2007)

[1] Master's Student, Department of Civil Engineering, Indian Institute of Technology Bombay, Powai, Mumbai, Maharashtra 400076, India, 213040078@iitb.ac.in, http://orcid.org/0000-0001-5702-5880

[2] Assistant Professor, Department of Civil Engineering, Indian Institute of Technology Bombay, Powai, Mumbai, Maharashtra 400076, India, albert@iitb.ac.in, http://orcid.org/0000-0002-4924-6592

3. Surveys and expert opinions involve gathering information from experts in the field or from workers themselves to make predictions about future productivity. (Shehata and El-Gohary, 2011)
4. The machine learning and artificial intelligence approach involve using algorithms and computational methods to analyze large amounts of data and predict future productivity based on that analysis. (Heravi and Eslamdoost, 2015)

Even though four of these approaches are available to estimate productivity, it is also important to note that a combination of these methods is often used to make the most accurate predictions about labour productivity. The estimation of labour productivity for any given activity is typically achieved by calculating the ratio of total output to total input, where input can be measured as either the total number of hours worked or the total number of workers involved. Alternatively, multifactor productivity, which accounts for both labour and capital inputs, can also be used as a measure of labour productivity (Rojas and Aramvareekul, 2003).

While these methods provide accurate measures of productivity for tracking ongoing projects, they pose challenges when attempting to predict the productivity of an activity that is still in progress. For instance, the total output of such an activity may be zero, but the work remaining to complete the activity may not be equivalent to the initial work remaining. This discrepancy can occur in practice when certain steps of the activity have been completed but do not contribute value to the project, resulting in a calculated productivity of zero. Although this consideration may not impact the actual performance of the site, it can significantly affect the planning and management of the remaining activities. Thus, it is important to carefully account for such nuances in productivity calculations for accurate project planning and management. Once the prediction of productivity is achieved for an activity, we can use it to implement lean in that construction activity.

Lean-based techniques are also employed to improve labour productivity in the construction industry. The various tools and techniques to implement lean in construction projects include 5S, Just in Time (JIT) and Kanban, work sampling, value stream mapping, Poke-Yoke, Takt-Time, and Kaizen with waste minimization as the key objective (Leksic et al., 2020, Singh and Kumar, 2020, Cossio and Cossio, 2012.; Sundararajaan and Madhavi, 2018; Tommelein and En Yi Li, 1999). The first step in the implementation of these tools is to identify the wastes involved and perform various analyses such as Pareto chart, failure mode and effects analysis (FMEA), process improvement and variation reduction to improve the process (Banawi and Bilec, 2014). Understanding labour productivity plays a major role in implementing lean and reducing waste in the construction industry (Serpell et al. 1994). Therefore, it is essential to estimate the actual productivity by assessing the effects of various influencing factors.

Even though the traditional productivity estimation techniques mentioned earlier and lean-based solutions have provided approaches to quantify productivity, there is a need to accurately predict the productivity of construction activities while they are being performed by also considering the power of lean construction. This study, therefore, proposes a novel framework to predict the absolute productivity of any activity, regardless of its current stage of completion. To achieve this, the study employs breaking down the activity into smaller sub-activities, enabling precise prediction of absolute productivity by also incorporating non-value-adding yet essential steps in productivity prediction. This is a notable improvement over traditional approaches that often exclude such steps. Furthermore, the study discusses the potential use of the framework in implementing the lean principle, which aims to reduce waste and optimize efficiency in the activity under consideration. This novel framework presents a promising approach to accurately predict and optimize productivity, offering potential benefits for various industries and applications.

LITERATURE REVIEW

Studies on labour productivity in construction typically focus on factors that impact labour productivity and methods for improving it. Several studies have found that the construction industry has low labour productivity compared to other sectors (Dixit et al., 2018; Rojas and Aramvareekul, 2012.), and this is due to several factors, such as poor project planning and management, a lack of standardization and modularization, and the inherent complexity of construction processes (Agrawal and Halder, 2020). Further, the factors that have been shown to impact labour productivity in construction include worker skill levels, job site conditions, the use of equipment and technology, and the availability of materials.

Some studies have also highlighted the importance of worker motivation and job satisfaction and have found that these factors can have a significant impact on labour productivity. Mistry and Bhatt (2013) conducted a survey in Gujarat, India and categorized the factors into four categories and found that the most affecting factors influencing productivity are the outside weather and delay in payment. Similarly, Doloi et al. (2012) selected fourteen factors and tried to develop a predictive model for labour productivity using Artificial Neural Network (ANN), adaptive-network-based fuzzy inference system (ANFIS), ANFIS-Genetic Algorithm and Random Forest algorithms. In this study, a predefined rating between one to five was taken for the factors. Likewise, Thomas and Sudha Kumar (2015) conducted an Indian case study for the same and explored the effects of some external factors, such as political instability, on labour productivity. Similarly, Enshassi et al. (2007) conducted their study in the Gaza Strip and concluded that work front unavailability is the top most factor that affects labour productivity, followed by a lack of proper planning. Overall, it can be seen that the site layout, crew composition and management-related factors are primarily found to affect labour productivity (Alaghbari et al., 2019; Doloi et al., 2012; Enshassi et al., 2007; Hamza et al., 2022; Hiyassat et al., 2016; Makulsawatudom et al., 2004; Nyoni and Bonga, 2016; Thomas and Sudhakumar, 2015). However, all these factors are exclusive of on-site tangible factors that directly influence the productivity of an individual activity. For instance, the different shapes of formwork in the formwork activity and cutting and bending length in the reinforcement activity. Several approaches can be witnessed in the literature about measuring the labour productivity of construction projects, but there are very limited studies on finding out the absolute labour productivity of any activity by incorporating all sub-activities.

Various studies have also found that construction labour productivity can be improved through better project management practices, such as the use of building information modelling (BIM) technology and the implementation of lean construction methods (Poirier et al., 2015) by streamlining construction processes, reducing waste, and improve communication and collaboration among stakeholders. Waste in construction can manifest in various forms, including overproduction, waiting, unnecessary movement, carrying excess inventory, and rework (Abbasian, Nikakhtar et al., 2012). Time studies and different process analysis techniques have been utilized to systematically identify and quantify waste in the construction process (Suresh, 2013). After identifying waste and its underlying causes, the next stage is to identify cost-effective opportunities for improvement that can be applied to reduce waste and improve productivity. This analysis is typically carried out through collaborative teamwork and brainstorming among team members (Serpell et al., 1994).

Overall, there is a need for a quantitative model that can predict labour productivity by incorporating the sub-activities and help implement lean techniques at construction sites. Therefore, this study presents a framework to predict absolute labour productivity for an activity. The two objectives of this study are given below.

1. To develop a machine learning-based labour productivity prediction framework based on the productivity of sub-activities that can help in tracking and re-arranging the flow of the activity.

2. To utilize the result of the framework to implement lean principles in the activity to increase its efficiency.

RESEARCH METHOD

To achieve the above objectives, a three-stepped research methodology is adopted that includes construction activity selection and analysis, productivity predictivity model development and the model's output to implement the lean principle.

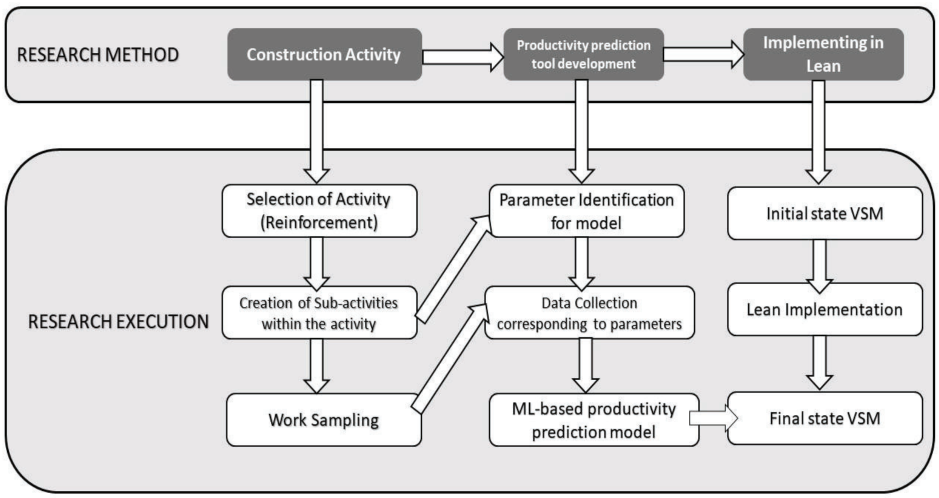

Figure 1: Research Methodology

The first step in research execution is analyzing a case study activity in detail and creating sub-activities. Activity is divided into sub-activities by capturing the actions that take significant time. By observing each sub-activity, the parameters that are affecting productivity are identified. Further, work sampling is performed for the entire cycle of the activity to collect relevant data for developing the machine learning-based multivariate linear regression method-driven predictive model for labour productivity using the parameters identified. A Value Stream Mapping (VSM) approach is then used to develop the detailed step-wise value stream map of the current state. Further, using the productivity values predicted by the productivity prediction tool earlier, a modified VSM is also developed. The detailed steps in identifying the sub-activities, work sampling, ML model development and performing VSM are explained below.

DIVIDING ACTIVITY INTO SUB-ACTIVITIES

The framework is applied at residential high-rise building construction sites in Mumbai. Reinforcement activity is analyzed, and it is then divided into sub-activities. This categorization is carried out based on the observation on site where the major time taking tasks are termed as sub-activities.

Table 1: Sub-activity categorization

Reinforcement Activity	
Sub-activity 1	Shifting and Cutting of Rebar
Sub-activity 2	Bending of Rebar
Sub-activity 3	Shifting to Workplace
Sub-activity 4	Laying and Fixing of Rebar
Sub-activity 5	Tying of Rebars

WORK SAMPLING

Once the sub-activities are formed, work-directed sampling is carried out to register the value of each activity in the sub-activities. This method involves observing employees performing specific tasks or activities. Observers record the activities being performed, and the data is later analyzed to determine the proportion of time spent on different tasks. The same is tabulated in the following table 2.

Table 2: Work Sampling for Reinforcement Activity

Sub-Activity	State
Cutting of Rebar	Shifting rebar to the cutting tool
	Measuring and cutting
	Shifting rebar to inventory 1
Bending of Rebar	Shifting rebar to bending Tool from inventory 1
	Measuring and bending
	Shifting rebar to inventory 2
Shifting to Workplace	Crane comes down from the 4th floor
	Idle time
	Crane loading
	Idle time
	Crane going up to the 4th floor
Laying and Fixing of Rebar	Shifting and laying of rebars
	Measuring and fixing rebar
	Idle time
Tying	Tying of rebars

PARAMETERS IDENTIFICATION

For the development of the absolute productivity prediction tool, input parameters are required. The parameters that are affecting productivity are shown below in Table 3. These parameters are tangible parameters collected from the construction site by visual inspection. Data is taken from a high-rise building construction site in Mumbai. Qualitative data are not considered here, so the productivity received is the absolute productivity for the considered activities.

Table 3: Identified Parameters table

Sub-Activity	Parameters
Cutting of Rebar	Number of rebars in one movement
	Diameter of the rebar
	Cutting the length of rebar
	The total length of the rebar cut
	Number of workers in the crew
	Weight of the rebar cut
	Percentage of skilled worker
	Time taken
Bending of Rebar	Number of rebars in one movement
	Diameter of the rebar
	The total length of the rebar cut
	Number of bends
	Number of workers in the crew
	Weight of the rebar bend
	Percentage of skilled worker
	Time taken
Shifting to Workplace	Height of the destination inventory
	Distance from crane placed to inventory
	The weight of the rebar shifted.
	Weight of the rebar bend
	Percentage of skilled worker
	Time taken
Laying and Fixing of Rebar	Diameter of the first type of bars
(Two different diameter rebars were used)	Diameter of the second type of bars
	Number of reinforcement bars of the first diameter
	Number of reinforcement bars of the second diameter
	Length of reinforcement bars of the first diameter
	Length of reinforcement bars of the second diameter
	The total length of reinforcement bars of the first diameter
	The total length of reinforcement bars of the second diameter
	Number of bends of reinforcement bars of the first diameter
	Number of bends of reinforcement bars of the second diameter
	Number of workers in the crew
	Weight of the rebar cut
	Percentage of skilled worker
	Time taken
Tying	Number of rebar joints tied
	Time taken

REGRESSION MODEL DEVELOPMENT

Regression models are developed using the above-mentioned parameters as input and the time required to carry out the sub-activity as an output. The first regression model for the cutting sub-activity is shown here. The input parameters shown as x1 to x5 are the diameter of the rebar, cutting length, rebar initial length, number of cuts and weight. The output parameter is the time required to carry out the sub-activity. A summary of the model is presented below in Figure 2.

```
[3]
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.949
Model:                            OLS   Adj. R-squared:                  0.945
Method:                 Least Squares   F-statistic:                     292.1
Date:                Mon, 03 Apr 2023   Prob (F-statistic):           2.05e-49
Time:                        06:29:22   Log-Likelihood:                -419.96
No. Observations:                  85   AIC:                             851.9
Df Residuals:                      79   BIC:                             866.6
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        219.5790     68.473      3.207      0.002      83.286     355.872
x1         -1.023e-13      2.339  -4.38e-14      1.000      -4.655       4.655
x2            79.7540     16.926      4.712      0.000      46.063     113.445
x3             1.2483      1.853      0.674      0.502      -2.439       4.936
x4            -5.3671      8.288     -0.648      0.519     -21.865      11.130
x5          5.384e-15      0.395   1.36e-14      1.000      -0.786       0.786
==============================================================================
Omnibus:                        2.028   Durbin-Watson:                   2.809
Prob(Omnibus):                  0.363   Jarque-Bera (JB):                1.939
Skew:                          -0.361   Prob(JB):                        0.379
Kurtosis:                       2.837   Cond. No.                     1.06e+03
==============================================================================
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Figure 2: Regression Model Result for Cutting Sub-activity

From Figure 2, we find the R-squared value as 0.949. That shows a good fit of the graph for the data entered. Eighty-five observations were used to develop this model.

IMPLEMENTATION AND RESULTS

The developed model is used to implement lean principles in the reinforcement activity. Value Stream Mapping (VSM) is used as a lean tool in this study. A current state VSM is developed from site observation which provides a snapshot of the current activity. Usually, in a VSM method, further, a future state would be developed based on assumed productivity values. Here in this study, the model developed above will be used to predict the productivities to be considered for developing the final state VSM.

CURRENT STATE VALUE STREAM MAPPING

For developing the current state VSM, a reinforcement activity is observed on the construction site. Data for developing the VSM is collected for each of the sub-activities, including idle time and wastage. The data collected is for 8.87 kg of rebar having a diameter of 10 mm and five bends. Figure 3 below shows the current state of the observed process.

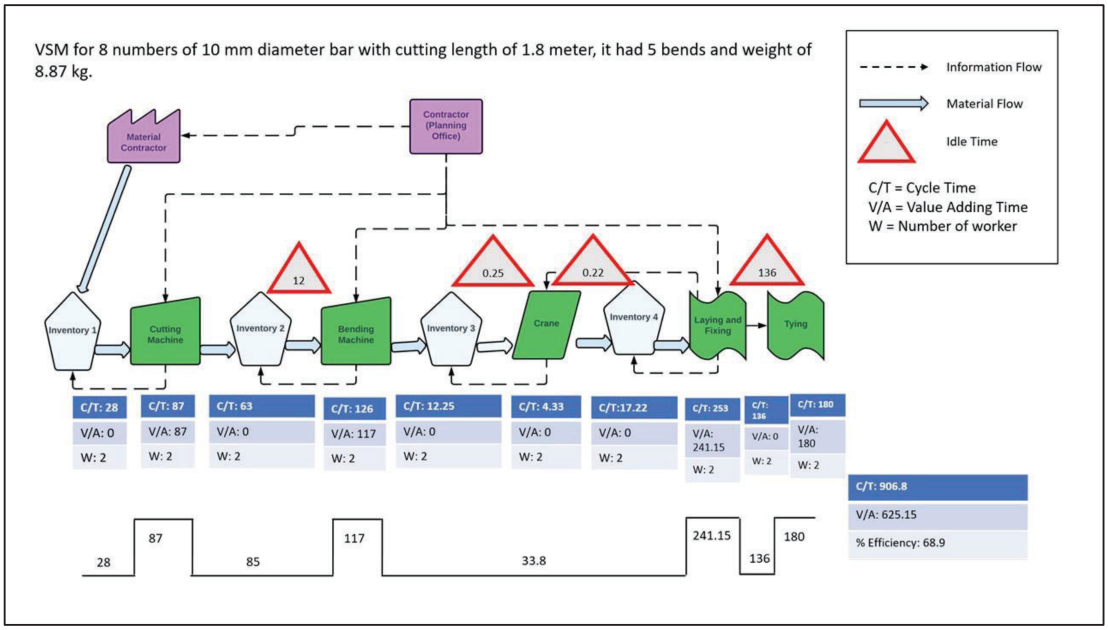

Figure 3: Current State VSM Diagram

PRODUCTIVITY OF EACH SUB ACTIVITY

For predicting the productivities of the sub-activities, multivariable linear regression is applied considering all the parameters shown above. The prediction was carried out for the same rebars in the current state VSM. Table 4 provides the details of predicted productivity values that are used to develop the future state VSM.

Table 4: Productivity prediction using regression analysis

Sub Activity	Workers in Crew	Productivity (kg/hr/crew)	R^2	Observations
Cutting	2	120.2	0.948	85
Bending	2	90.17	0.943	85
Shifting (Crane)	3	7673	-	17
Laying and fixing	2	51.43	0.915	85
Tying	2	147.8	-	35

As per the productivity obtained by the study, there are significant differences between the productivity of sub-activities. So, to remove some of the inventory from the current state of VSM, we need to match the productivity of sub-activities. That will make the activity more efficient as the material can be shifted to the sub-activity without going to inventory.
Here it can be seen that the productivity of cutting is 120 kg/hr and that for bending is 90 kg/hour, so if four crew for bending and three crew for cutting are assumed, the productivity of the process will be the same, and materials could be directly shifted to bending after cutting without using an inventory. In addition, after reducing the idle time, the final state VSM is proposed below, which is developed using the predicted productivity values.

PROPOSED FINAL STATE VALUE STREAM MAPPING

The final state VSM is developed using the predicted productivity values given below.

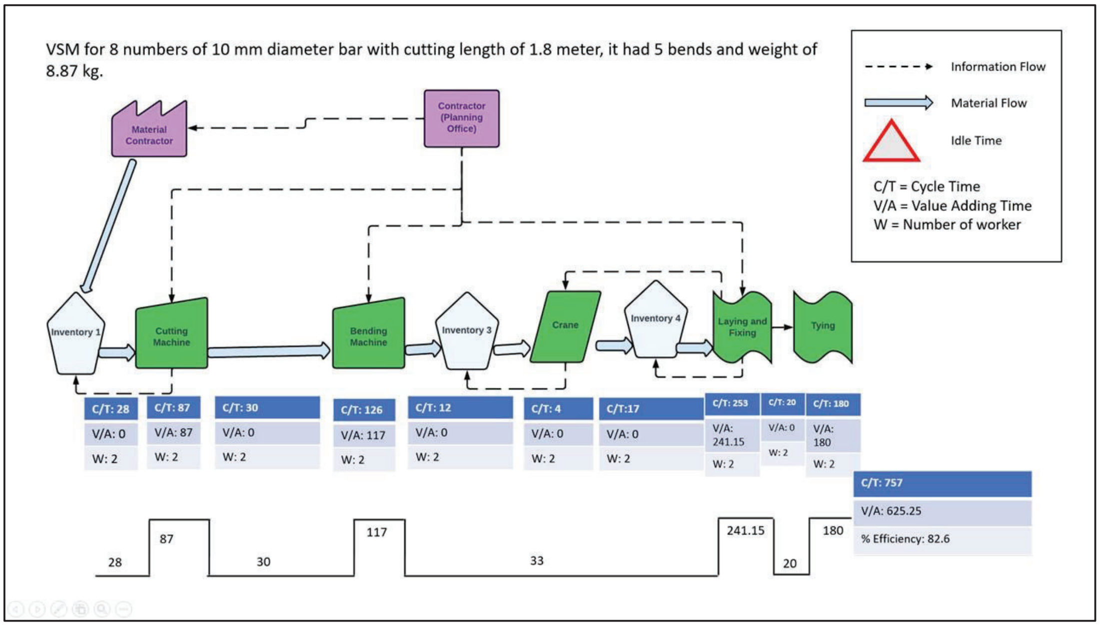

Figure 5 Final State VSM

As was discussed above, it is proposed to remove inventory 2, which is there between the cutting and bending sub-activity. It reduced the time between these sub-activities by 64%, and it also reduced one worker that was shifting the material to inventory. The overall efficiency of the activity, which was 68.9% in the current state VSM, is now 82.6% in the proposed state VSM after applying the lean principle and using the productivity prediction approach.

DISCUSSION

In this study, a labour productivity prediction model is developed using data from a construction site. The model is designed to accurately forecast the absolute labour productivity for upcoming reinforcement activity tasks. Subsequently, the model is utilized to implement lean practices in the activity. The predictions from the model indicate that there is room for improvement, and just-in-time techniques can be implemented by matching the productivity of workstations.

The current state Value Stream Map (VSM) for the activity resulted in a cycle time of 906 seconds. However, when the model's results are used to increase the number of bending workstations relative to cutting workstations, it is possible to reduce inventory and achieve a cycle time of 757 seconds. This demonstrates that utilizing the model can lead to a significant increase of 13.7% in activity productivity. This finding highlights the potential of the labour productivity prediction model in improving construction site efficiency and performance.

CONCLUSION

The construction industry is of labour-intensive nature, and there is a strong need for achieving improvements in the labour productivity aspect. However, the current practice of labour productivity calculation falls short of providing accurate productivity estimates for activity planning, especially when activities are partially completed. To address this gap, this study proposed a novel framework that utilizes the productivity of sub-activities within an activity to predict the absolute productivity of the entire activity.

The proposed framework offers an efficient approach to organizing resources and implementing lean principles, thereby enhancing the overall productivity of the construction project. Through the implementation of the framework, a notable improvement in productivity of 13.7% is demonstrated. It is worth noting that the framework has the potential to further enhance its predictive accuracy by incorporating deep learning algorithms. However, the implementation of such algorithms may require a substantial amount of data sets, making them more suitable for large-scale projects with ample data availability.

In conclusion, the framework presented in this paper addresses the limitations of current labour productivity calculation methods and provides a promising approach for predicting activity productivity in construction projects. The demonstrated improvement in activity productivity highlights the potential of the proposed framework in optimizing labour productivity and promoting the adoption of lean practices in the construction industry. Future research can further explore the integration of advanced algorithms to enhance the accuracy and applicability of the framework and investigate its effectiveness in different construction activities, contexts and project scales.

LIMITATIONS AND FUTURE WORK

The present study exhibits certain constraints which need to be addressed in future research endeavours. Firstly, the study's input parameters are limited in number, thereby failing to account for intangible inputs such as labour fatigue, management practices, and on-site safety factors. The exclusion of these inputs may hinder the accuracy of the prediction model. Thus, their inclusion could potentially enhance the efficacy of the prediction model.

Moreover, the study's prediction model only accounts for absolute productivity during reinforcement activities. However, to employ the model for project planning, it is imperative to consider labour efficiency. Therefore, the model's utility for project planning purposes needs further examination. It is noteworthy that the regression model employed in this study demonstrated satisfactory performance. Nevertheless, the applicability of other deep learning models must be explored for construction activities, especially if the results from the present model are suboptimal.

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