Impact of Reinforcement Design on Rebar Productivity

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Abstract –

Scheduling is an essential part of project management, and many processes like procurement, fabrication, and resource mobilization are based on these schedules. If the actual targets lag from the pre-planned schedules, waste is generated in the form of idle inventory. It also results in an increased workload on man and machinery, leading to errors and rework. Schedules are impacted by unreliable productivity estimates assumed during planning stages. In construction, project productivity can vary based on several factors. Reinforcement productivity is affected by factors like site layout, labour skill, design, learning effect, etc. The impact of reinforcement design on productivity is poorly studied, especially in heavily reinforced structures. Thus, the main objective of this study is to validate the hypothesis that reinforcement design affects productivity, which can be used to predict productivity for future structures. The methodology for this study is divided into 3 phases; 1st phase involves data collection and literature review, 2nd phase involves modelling rebar productivity by data fitting models to understand the factors of reinforcement design that affect productivity. MATLAB and Microsoft Excel are tools used in the data fitting process. In the final phase, based on this model, appropriate actions are suggested to improve productivity. Discussion on the aspects of reinforcement design that are found to have an impact on productivity is also detailed.

Keywords –

Reinforcement productivity, Data fitting, Regression analysis, MATLAB, Excel, heavily reinforced structures, rebar density, complexity in design, Delay, work productivity, Buildability, Rebar placement, lean construction management.

1 Introduction

The lean methodology's core concept involves identifying waste and reducing or eliminating it. This study deals with waste due to improper planning and scheduling. Scheduling is the process of planning and arranging various activities to optimize resource utilization.

The main challenge in preparing a schedule is estimating the time required for completion, which involves predicting productivity. Productivity is affected by several factors like weather, site layout, labour skill, etc. [1]. The literature study found that the effect of reinforcement design on productivity, especially in heavily reinforced structures like industrial structures, bridges, and power plants, is not well understood.

Figure 1 shows the productivity variation for reinforcement placed at a construction site with heavy reinforcements. The graph found that for three months, between September – November 2021, the productivity varied between 0.025 MT/man-day to 0.076MT/man-day with an average of 0.055 MT/man-day and a standard deviation of 0.0108MT/man-day. This variation in productivity was seen even when external factors like site layout/weather/labour skills were constant. So, it would be reasonable to deduce that some inherent factors about certain structures affect productivity.

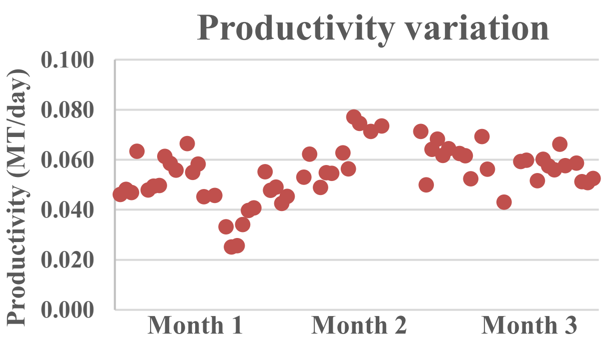

Figure 1. Productivity variation was observed for reinforcement placed at the site.

This paper hypothesizes that heavy reinforcement influences productivity, and using data modelling, this relationship is demonstrated, and an attempt is made to predict productivity based on specific design parameters.

The site chosen for the study is a structure subjected to heavy loads and characterized by large and closely spaced heavily reinforced columns with deep beams. Some critical parts of the structure have reinforced concrete walls with heavy reinforcements. Numerous embedded parts in the concrete structures enable the installation of ducts, pipes, and cables. The shape of the structure is complex and varies from floor to floor. Figure 2 shows an example of a heavily reinforced slab for a structure with an opening to understand better the challenges faced at the site.

Figure 2. Representative picture of heavy reinforcement taken by the author at a similar construction site.

From the literature review, several studies have been found that list the various factors that affect productivity. However, most of these studies deal with residential/commercial projects and focus on factors like equipment, labour efficiency, and construction methods to improve productivity [2]. Very few papers explore challenges in heavily reinforced structures.

Although past studies list design as a factor affecting productivity, they do not explain and model what aspects of design affect productivity. Thus, the objectives of this study are as follows:

- To develop a method to help predict the productivity of structures based on reinforcement design to validate the hypothesis that reinforcement design affects productivity in heavily reinforced structures.
- Identify possible reasons for low productivity for heavily reinforced structures and suggest appropriate measures to deal with the same.

In terms of structure, this paper is broadly divided into seven sections. After the introduction, Section 2 discusses the literature review. Section 3 highlights the methodology used. Section 4 details the data fitting principles and complexity parameters. Section 5 deals with the data fitting models considered. Section 6 presents the result and analysis of the developed models. Section 7 presents the limitations and future directions. Finally, the study is concluded in Section 8.

2 Literature Review

In the construction industry, lean construction first appeared in 1992 [3] and has been applied to several construction sites [4]. According to B. Jørgensen et al. [5], in general, all methods encompassing lean construction focus on some common elements like reducing waste concerning the end customer expectation, managing the supply chain from a demand-pull approach, approaching production through a focus on processes and flow.

Literature shows that schedules are one of the most critical success factors contributing to the success of a project [6]. Unrealistic schedules cause waste in excess inventory and idle time and pressure men and machinery to achieve unrealistic targets, leading to safety and quality issues.

Accurate productivity rates are needed to have accurate schedules, but in construction, productivity is affected by several external and internal factors [7]. Based on a questionnaire study, Parthasarathy et al. [8] have found several factors that might affect productivity in tall residential building constructions. They have ranked them based on their relative importance. They reported improper planning and scheduling as the leading cause of productivity issues [9].

Rebar fixing is one of the essential activities generally seen in construction, accounting for the most significant percentage of the cost and time of total construction, especially in heavily reinforced structures [10]. There are studies for productivity improvement for activities like formwork, concreting, and blockwork [11,12], but a comparatively lesser number of studies focused on reinforcement [13]. One such study documents the challenges faced in nuclear construction due to the high reinforcement density in reactor building constructions and subsequent issues due to loss in productivity and quality [14].

Though the literature suggests reinforcement design as a factor that can affect productivity [15], it doesn't detail or quantifies what characteristics of reinforcement design causes productivity issues, especially in heavily reinforced structures. This study tries to fill this gap by modelling and predicting productivity using data-fitting software.

To model productivity, machine learning, neural networks, simulation software, and regression analysis have been suggested by various studies [14,16–18]. Based on different factors, this study tries to model productivity using regression analysis of complex factors defined based on inputs from the site.

MATLAB is a software developed by MathWorks primarily for numerical computing. It has features that can automate data fitting, like the fit command [19]. The curve fitting toolbox is an add-on to MATLAB software which makes the curve fitting process more interactive and brings in more functionality [20]. This study will use these features to model productivity data based on factors in section 4.

3 Methodology

As shown in Figure 3, the study is divided into 3 phases. The 1st phase involves a basic literature review and site consultations to understand the current situation on the topic. The second phase involves data collection, defining complexity parameters for various concrete elements, and then using fitting data software to fit a surface using the complexity parameters as independent variables and productivity as the dependent variable. The model is also validated with independent data.

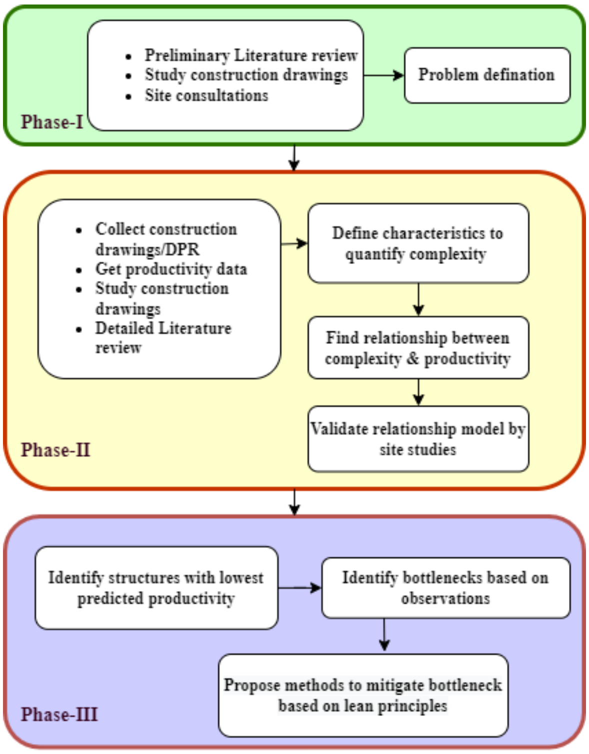

Figure 3. Methodology flowchart

In the final phase, the validated models were then used to predict productivity for concrete elements scheduled in the future. Based on the analysis of the model and predicted productivity, appropriate measures to improve schedules are discussed. The data is also analyzed to understand the factors of reinforcement design that affect productivity, and some conclusions are drawn.

4 Curve Fitting

We can see significant variations between different structures from the productivity data, but it is difficult to understand why one structure might have better productivity over the other. The reinforcement design affecting productivity can be quantified and better explained using data fitting models and predicting productivity values.

The first part of data fitting is identifying the dependent and independent variables to isolate them.

4.1 Data collection procedure

As productivity is affected by multiple factors other than design, to have a good prediction model, it is required to isolate the data which are only affected by the factors that are of interest to this study. To achieve this, the following steps were taken during data collection.

1. The test data was collected within a short span of 2 weeks, and it was ensured that the weather-related factors did not vary for the data points.
2. All the data were collected from a similar elevation, thus eliminating variation due to equipment bottlenecks like cranes.
3. Distance between the stockpile and work area was similar for most of the data points, thus eliminating variation due to site layouts.
4. The lack of materials and operational delays did not affect the data points.

4.2 Converting subjective metrics into numerical factors

Complexity is subjective; when comparing two structures, one can be estimated to be more complex, but quantifying that difference is a difficult task. Discussions were conducted with multiple foremen at the site, and the following points were noted to be factors affecting productivity.

1. Large diameter bars and long bars are heavier and more difficult to handle at the site where space is limited.
2. Rings and stirrups for columns and beams are more difficult to place when compared to main bars.
3. Heavy reinforcement and congestion make inserting stirrups/shear/column ring difficult.
4. Openings in walls increase the number of bars, and rework will be needed when reinforcement fouls with openings. Thus, increasing complexity.
5. Different reinforcement spacing in a structure requires additional marking and placing reinforcement.
6. Joggling of reinforcement is needed in beams to prevent fouling with reinforcement of intersecting beams and columns.
7. The nonlinear shape of the structure, short-length walls, and non-standardized column dimensions add to confusion and complexity.

To convert these factors into a quantifiable number, some approaches in literature were studied, like a point system to determine a score to define various properties for rebar bending, which was then subsequently used in a classification algorithm [17]. In another study, a metric like the weight of reinforcement per unit of concrete to define congestion was used to compare congestion between nuclear construction and typical construction [15]. Based on literature analysis and site experience, several different parameters were analyzed. The following two factors were the best representation of the subjective factors as they were directly related to the complexity of heavily reinforced structures.

1. **Parameter 1 - Density of reinforcement:** This parameter is the ratio of the weight of reinforcement to the volume of concrete for the structure in question (in MT/cum). The weight of reinforcement is calculated based on the bar bending schedule provided by the designer or BBS procured from the steel yard. The weight of concrete is obtained by considering the dimensions and openings of the structure. This parameter accounts for the close spacing of reinforcements, the diameter of reinforcements, congestion, and the length of bars. This parameter shall be denoted as 'P1'in this paper.
2. **Parameter 2 - Non-linearity of reinforcement:** This parameter is the ratio of the number of bends of all bars to the total length of reinforcement for a given structure multiplied by 10 (in bends/10m). The total length and number of bends are extracted from the BBS. This parameter accounts for complexity due to stirrups/column rings, openings, short wall sections, complex wall shapes, and reinforcement joggling. This parameter shall be denoted as 'P2'in this paper.

The two parameters defined above consider most of the subjective metrics described above and, according to this study, are assumed to represent the complexity of reinforcement wholistically.

4.3 Calculating the parameters

To calculate the two parameters for a particular structure, the following four values must be first estimated: concrete volume, reinforcement weight, reinforcement length, and the number of bends in reinforcement. These values can be obtained manually from the bar bending schedule (BBS) provided by the designer. Alternatively, with the help of a Revit model, the BBS can be exported into a .csv file, which can then be read using MATLAB. Data fitting can be done automatically to have a continuously updated model.

5 Data Fitting Models

Depending on the process, data modelling could be parametric modelling (E.g., Regression modelling) or non-parametric modelling (E.g., Interpolation). In this study following two models were developed.

- **Polynomial model:** Regression analysis is a set of statistical processes for estimating the relationships between one or more independent variables. Polynomial regression analysis is a multiple linear regression analysis case where the relationship between dependent and independent variables is modelled as an n^{th}-degree polynomial function.
- **Interpolant model:** Interpolation is a method to connect discrete data points to get reasonable estimates of data points between the given points. Depending on the surface required, one or more functions can be used to estimate values between data points. It is also possible to extrapolate data outside the original dataset using splines.

5.1 Determining the best fit

During the data collection, several precautionary steps were taken to remove the influence of factors other than the design parameters. But due to the nature of data collection, there will always be errors in the data even after taking these precautions. Generally, a metric called the coefficient of determination (R^2) determines how well the predicted values match the actual values assuming the data is accurate with only slight variations. But as explained by Prakash R [21], it was found that the measured productivity deviates from actual productivity due to measurement errors.

For a given set of data points, creating multiple surfaces with varying R^2 values is possible. To determine the best fit, two approaches can be taken.

1. The easiest method is to find the surface with the highest R^2 value; this method assumes the test data is accurate and no other factors influence it. However, we know from the literature that productivity is affected by multiple factors, and even though some of the factors are accounted for, some data points might distort the data.
2. Comparing possible models with data independent from the data set used to make it is also a viable method to determine the best fit. This method is used in this study to determine the best fit.

5.2 Curve fitting using MATLAB

MATLAB offers various methods to fit data by parametric and non-parametric models. The curve fitting toolbox available in MATLAB is one such tool that lets you perform exploratory data analysis and compare candidate models. The toolbox also supports non-parametric modelling techniques, such as splines, interpolation, and smoothing [19,20].

After creating a fit, one can apply various post-processing methods for plotting, interpolation, and extrapolation, estimating confidence intervals, and calculating integrals and derivatives.

6 Result of Data Fitting, Validation, and Discussion

The test data was added to the MATLAB workspace, and using the curve fitting toolbox, the following models were developed:

6.1 Polynomial modelling (parametric)

The polynomial function with the best R^2 rating for the data is:

$$f(x, y) = 0.06299 + (0.01943 * x) - (0.01943 * y - 0.006567 * x^2) + (0.00145 * x * y) + (0.00145 * y^2) + (0.002058 * x^3) - (0.00113 * x^2 * y) - (10^{-5} * x * y^2) - (7.5 * 10^{-5} * y^3) \quad (1)$$

Where 'x' refers to the P1 (rebar density) and 'y' refers to the P2 (non-linearity), and f gives the predicted productivity, Figure 4 and Figure 5 shows the 3D and contour plots of the polynomial model.

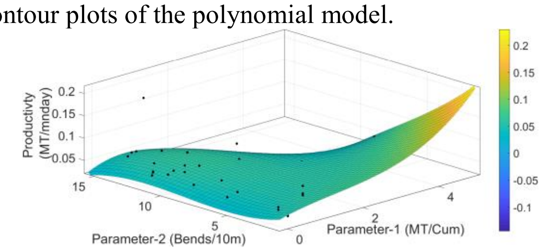

Figure 4. Polynomial model 3D plot

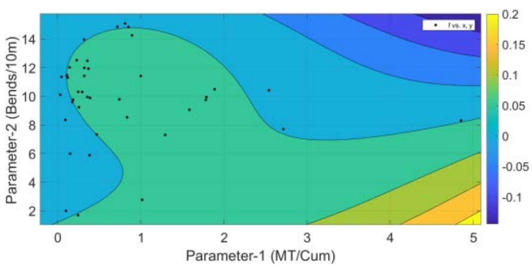

Figure 5. Polynomial model contour plot

Table 1 shows the productivity for eleven independent data points from January to validate the model, compared with the corresponding predicted productivity.

From this data, the predicted productivity varies from actual productivity. This variation is up to 25% of the productivity. Still, for five of the eleven data points, the variation was within ±10% of the productivity, considerably less than the variation seen in the non-parametric model. Thus, it is better at predicting productivity than the non-parametric model.

Table 1. Validation of the polynomial model

Structure	P1	P2	Productivity (MT/man-day)		Var.
			Act.	Pred.	
Column1	0.05	11.3	0.05	0.0482	7.31%
Wall 1	0.19	13.8	0.04	0.047	-11.90%
Column2	1.81	9.68	0.06	0.0571	1.55%
Column3	1.48	13.7	0.05	0.0521	-6.33%
Column4	2.74	8.97	0.05	0.0451	-0.22%
Column5	2.03	8.14	0.05	0.0546	-21.33%
Column6	4.10	8.65	0.04	0.0351	14.39%
Column7	4.29	8.59	0.05	0.0363	21.09%
slab1	0.52	8.64	0.07	0.0545	25.34%
column8	0.30	10.3	0.04	0.054	-22.73%
column9	0.39	9.88	0.06	0.0552	1.43%

6.2 Interpolant modelling (non-parametric)

For the interpolant modelling, the thin plate spline method was chosen so that the extrapolation of data was possible. Figure 6 and Figure 7 show the 3D plot and the contour plot of the interpolant model.

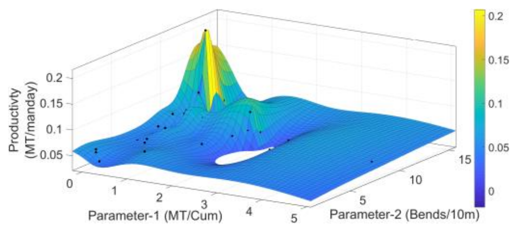

Figure 6. Interpolant model 3D plot

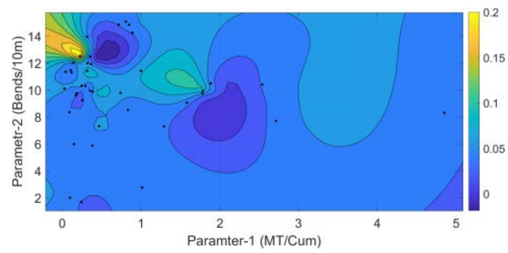

Figure 7. Interpolant model contour plot

Table 2 shows the productivity for eleven data points from January compared with the corresponding predicted productivity.

From this data, the predicted productivity varies from actual productivity. This variation is up to 217% of the productivity. For only two of the eleven data points, the variation was within ±10%, considerably more than the variation seen in the parametric model. Thus, even though this model is a better fit for the data, it is poorer at predicting productivity than the parametric model.

This can be because the test data contains certain data points that are too erratic and influenced by factors irrelevant to this study, thus skewing the model in the vicinity.

Table 2. Validation of interpolant model

Structure	P1	P2	Productivity (MT/man-day) Act.	Productivity (MT/man-day) Pred.	Var.
Column1	0.05	11.3	0.05	0.0490	5.77%
Wall 1	0.19	13.8	0.04	0.1332	-217.14%
Column2	1.81	9.68	0.06	0.0481	17.07%
Column3	1.48	13.7	0.05	0.0745	-52.04%
Column4	2.74	8.97	0.05	0.0496	-10.22%
Column5	2.03	8.14	0.05	0.0047	89.56%
Column6	4.10	8.65	0.04	0.0603	-47.07%
Column7	4.29	8.59	0.05	0.0576	-25.22%
slab1	0.52	8.64	0.07	0.0635	13.01%
column8	0.30	10.3	0.04	0.042	4.55%
column9	0.39	9.88	0.06	0.0685	-22.32%

6.3 Limitation of models

Even though data fitting models can predict productivity with some accuracy, the absolute productivity values are only valid if no new factors get involved. In addition to this, some other limitations were noted for both these models, like,

- Parametric model: Parametric models help understand the general relationship between the variables, but they may not give a perfect fit, especially for data with a high amount of variability. As the initial data set used for creating the model will be limited to a certain range based on the structure, predicting productivity for structures with parameters outside this range is difficult.

- Non-parametric model: As non-parametric models do not provide a function as an output, it is difficult to interpret compared to parametric models. Also, to predict/visualize the model, MATLAB application/other software is needed. It was also observed from the model that the non-parametric model was less reliable than the parametric model in this scenario.

6.4 Automating data fitting procedure

Calculating the design parameters and data fitting in MATLAB can be automated using Revit and excel. The bar bending schedule can be exported from Revit as a .csv file which can then be read using MATLAB. MATLAB can be coded to predict productivity or to automate data fitting to keep the model up to date.

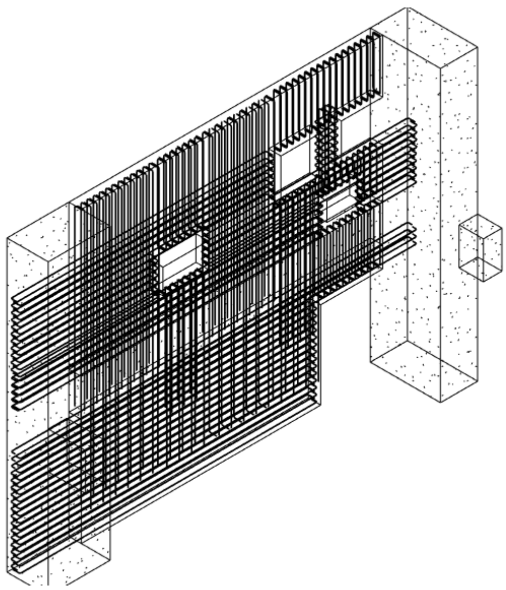

Figure 8: Revit model

Table 3: Sample BBS obtained from Revit.

Bar Mark	Type and size	Quantity	Length of each	Shape code	A* mm	B* mm	C* mm
1	H12	12	4375	11	4205	205	0
2	H12	11	6500	11	6345	180	0
3	H12	14	4350	11	4205	180	0
4	H12	5	6525	11	185	6350	0
5	H12	14	2175	21	180	1860	180
6	H12	34	1525	21	180	1210	180
7	H12	4	2050	21	165	1740	180
10	H12	6	3250	11	3095	180	0
11	H12	8	4300	11	4130	180	0
12	H12	6	2700	11	2540	180	0
13	H12	8	3800	11	3650	180	0

6.5 Characteristics of reinforcement affecting productivity

The two models shown above can predict values for a better understanding of the factors affecting productivity. A classification system was used to understand better the variation of productivity based on the variation of independent parameters.

In this method, the dependent variable, independent variable, and productivity are classified into three categories, i.e., below average, average, and above average (Table 4 shows the limits for each variable). The result was then analyzed to find any trends in the data. Classification helps minimize variations in the data by clubbing a similar range of data together.

Table 4. Classification limits

	Below average	Average	Above average
Productivity (MT/man-day)	≤ 0.04	0.04 to 0.06	≥ 0.06
Rebar density (MT/Cum)	≤ 0.25	0.25 to 1	≥ 1
Non-linearity (Bends/10m)	≤ 4	4 to 10	≥ 10

Table 5 shows the result of classifying 64 data points into the abovementioned categories. From this table following are the observations.

1. For a given reinforcement density (except for light reinforcement), productivity tends to decrease with an increase in non-linearity. The aberration in light reinforcement could imply that non-linearity is relevant only for heavier reinforcement.
2. For a given non-linearity, productivity tends to increase with reinforcement density.
3. By analyzing various structures, this can be explained by the following observations. Data points considered in this model refer to structural elements like columns, beams, walls, and slabs. With column and beam forming, most of the data points were collected.
4. In a column/beam, there are generally two reinforcement bars, a reinforcement element parallel to the length of the structure (main bars) and reinforcement perpendicular to the length (stirrups, rings, etc.). Main bars are generally larger in diameter and are easier to fix in place as they are usually long and straight. Stirrups/rings, on the other hand, are of smaller diameter and take longer to fix in position, thus reducing productivity.
5. A structure with high density will have a greater number of main bars (as the contribution of rings to density is less than the main bars), resulting in better productivity. A structure with high non-linearity will have multiple sets of rings (as main bars are primarily straight, contributing less to the non-linearity parameter), thus reducing productivity.
6. The classifier model helps understand the relationship between the various factors but cannot predict productivity values like the other models. It can only comment on the range of possible productivity.

7 Limitations and Future work

- A more extensive study with a greater data sample would be necessary to enhance the model's accuracy.
- Considering that various factors influence productivity, the model would require regular updates to accommodate environmental changes, production technology, methods, specifications, logistics, labour skills, etc. The frequency of these updates could be determined based on data collected from a more comprehensive study [22].
- Machine learning-based models will be utilized to model and forecast productivity.

8 Conclusion

From the models developed, it can be concluded that reinforcement design does affect productivity and can be predicted. Other conclusions that can be drawn from this study are:

- Contrary to popular belief, large-diameter heavy reinforcement (high P1 value) does not lead to a loss in productivity; instead, it increases productivity.
- Loss in productivity is seen when the number of bends in the reinforcement increases. So short walls, nonlinear walls, the presence of openings discontinuation in reinforcement, presence of stirrups/column rings affect productivity, especially for structures with a density of more than 0.25MT/cum.
- This study showed that this productivity could be predicted using data fitting models, provided all other factors remain the same.

Table 5 Result of classification.

Density	**Non-linearity**								
	Below average			**Average**			**Above average**		
Below average	2	3	-	3	3	-	1	6	3
	40%	60%	-	50%	50%	-	10%	60%	30%
Average	-	-	-	2	5	5	1	7	4
	-	-	-	17%	42%	42%	8%	58%	33%
Above average	0	3	2	-	10	1	-	3	-
	0%	60%	40%	-	91%	9%	-	100%	-

- This model was also validated using independent data.
- Using the predicted productivity values, schedules can be better optimized to balance low and high-productivity structures.

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