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Investigation of Pile Construction and Productivity Loss: An Analysis of Macro Impact Factor

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Abstract

Pile foundations are challenging to build due to subsurface obstacles, contractor ignorance, and difficulties with site planning. Given the unpredictable environment of the construction site, productivity losses during pile work are to be thought possible. Prior to finishing a site pre-investigation, a foundation's area is usually sampled for statistical reasons. There are studies on pile construction outside of Bangladesh that are supported by relevant empirical data in the literature. Since Bangladesh, which is regarded as a third-world country, is ignored in this regard, the literature currently available about pile building and the associated productivity loss is unable to provide adequate information or appropriate empirical data. Due to this pile-building sector in Bangladesh has been experiencing a decline in production for quite some time now. Before attempting to increase productivity in pile construction, it is essential to investigate the potential losses and the variables that might have an influence. This study aims to accomplish the following objectives: 1) identify the primary factors that have an impact on pile construction; 2) develop an SVR model that accurately predicts productivity loss; and 3) figure out the projected loss by basing it on the historical scenario that is the most comparable to the current one. A Support Vector Regression (SVR) model was developed after a study of the relevant literature. This model enabled the collection of 110 pile building projects from five significant locations in Bangladesh. The model was constructed using a list of eight inputs in addition to a list of five macro elements (labor, management, environment, material, and equipment) (soil condition, pile type, pile material, project size, project location, pile depth, pile quantity, and equipment quantity). Using 10-way cross validation, the SVR achieves an accuracy of 87.2% in its predictions. On the basis of what has occurred in the past, we are able to estimate that there will be a loss of around 18.55 percent of the total output. A new perspective for engineers studying the delay factors with productivity loss is provided by the outcome of important tasks as it relates to loss in productivity and overall factors faced. In the building construction industry, effective management should place more emphasis on the correlation between productivity loss and the factors that cause it. Therefore, to represent the effect on productivity loss, real factors can be summed up as a decline in productivity loss. The findings of the study would urge specialists to concentrate on waste as a means of increasing overall production.

Keywords

Productivity Loss, Macro-Effect Factor, Pile Construction, Regression Model, SVR Model

1. Introduction

Productivity can be defined as the connection that exists between a system's output and the input required to produce that result. There are many different types of inputs, including laborers, money, energy, and materials. When these resources are used, outcomes like products and services are created. The construction sector worldwide is extremely concerned about productivity loss in pile construction. It refers to the decline in productivity and efficiency observed during the construction of piles, which can cause project delays, increasing expenses, and poor quality work. This review of the literature tries to examine current research on productivity loss in pile construction, both globally and in the context of Bangladesh. This review highlights the need for empirical data that is particular to the construction industry in Bangladesh by analyzing the present literature to highlight knowledge gaps. Numerous researches examined at productivity loss in pile construction, offering helpful details on the variables affecting effectiveness [1]. For instance, study in Singapore found that resource limitations, poor site management, and inadequate planning are the key contributors to productivity loss in pile construction [2]. Similar to this study, productivity concerns elements in pile foundation construction in Indonesia, including weather, site accessibility, and equipment availability had a big impact on production levels [3]. Research was conducted on additional international study to examine the connection between labor productivity and various variables in pile construction projects in Hong Kong. According to the research, the main causes of lost productivity in the construction industry were insufficient staff, supervision, and coordination.

Developed nations have struggled with the issue of how to gauge productivity in the building sector since the 1960s. [4] evaluates earlier research on construction productivity and compares it to more modern methods of quality measurement in order to give guidance for using performance data from construction projects. [5] claim that using a sample of industrial projects, productivity measures can be created and should be useful in evaluating construction productivity. In conclusion, based on the previous research, 19 variables are chosen and classified into the following 5 groups: labor, management, environmental, material, and equipment [6]. According to Huang, there are three distinct productivity levels in the construction business: task level, project level, and industry level. According to Park [5], construction productivity rates vary between projects because of the various environments, characteristics, and project management efforts for each project. For this reason, the emphasis of our study will be on project level productivity. As a result, when examining construction productivity, one should take into account the factors that contribute to variations in productivity between jobs. Although strategic levels of management were essential in boosting building productivity, Chan and Kaka [7] proceeded further in their justification for project-based measurement of productivity by emphasizing the need to connect it to the projects themselves. In support of this, they cite Groak [8], who claims that industry failed by not acknowledging the project location as the "defining locus of production organization." This meant that the sector needed to refocus its efforts on improving output on the projects, and in order to do this, measurement is essential.

Equipment damage was the main factor that had an impact on pile construction activities in Bangladesh. This led to idle time and significantly lower production. The second element that greatly reduced productivity, according to [9], was labor because workers frequently take breaks outside of the designated break period, resulting in idle time. According to an impressive industry study by Winch [10], low worker morale led to lower production. In their research on productivity measurement, Santosh and Apte [11] also found that workers were motivated by receiving feedback on their performance. Operator effectiveness, weather, site conditions, work management, soil removal system, pouring system, mechanical challenges, owner and/or consultant issues, site inquiry, and productivity estimate accuracy are the ten productivity variables that provide a quantitative assessment. The impact of each of these ten factors can be broken down into a variety of different categories or attributes. However, this analysis focuses only on the ten major factors without taking into account the supporting variables or attributes [12]. The macro environmental forces that impact an organization's performance and strategies include the natural environment, political and legal environment, economic environment, demographic environment, and cultural environment [13].

The most popular statistical method for predicting output is the regression model [14]. Using this method, one can establish productivity predictions based on actual productivity data and determine the impact of different factors [15]. Regression models were used by Hanna *et al.* [16] to investigate how change orders affect construction output. To describe how weather affects construction productivity, Koehn and Brown [17] developed non-linear equations. According to the learning curve theory, productivity will increase over time as a result of increased familiarity with the task, better administration, and more effective tool and equipment use [18] [19] [20]. In order to forecast productivity, mathematical learning curve models have been created. For resolving classification and regression issues in a variety of subjects, Support Vector Regression (SVM) has emerged as a major learning technique [21]. To maximize hyperplane and input data into a support vector is the idea behind SVR. Being able to avoid overfitting is the only benefit of SVR [22]. Meanwhile, SVM's benefits include its capacity for generalization, dimensionality curve, feasibility, powerful implication ability, quick learning speed, and capacity for precise prediction [23].

Despite the fact that these studies from other countries offer insightful information about productivity loss in pile construction, it is important to acknowledge that the Bangladeshi context may bring particular difficulties that call for special consideration [24]. In contrast to other nations, Bangladesh's construction sector operates under unique conditions, including varied labor laws, legal frameworks, and socioeconomic factors, all of which may have an impact on productivity. Unfortunately, there is limited research on productivity loss in pile construction in the context of Bangladesh. However, a few studies that focus on specific areas of productivity loss in Bangladesh's building industry can provide initial insights. For instance, a study on the variables influencing productivity in Bangladesh's construction industry was undertaken [25]. Despite the fact that the study did not focus solely on pile construction, it did identify labor shortage, inadequate project planning, and a lack of sophisticated construction techniques as major factors in productivity loss. While this study offers an initial guide, more investigation into pile construction in Bangladesh is necessary to acquire a better understanding of the difficulties encountered in this particular industry [26].

There are certain significant gaps that require filling in the existing research on productivity loss in pile construction, both internationally as well as in Bangladesh. First off, there aren't many empirical studies that focus on the Bangladeshi context. The majority of research either concentrates on difficulties related to general construction productivity or look at pile construction in other nations. Research that explicitly examines productivity loss in pile construction within this environment is necessary due to the distinctive characteristics of the Bangladeshi construction industry, including local labour practices, cultural issues, and legal frameworks. Additionally, a thorough research of the factors affecting productivity loss in pile construction in Bangladesh is required. It is important to comprehend how these factors emerge and interact within the Bangladeshi context, even though some worldwide studies have identified common reasons of productivity loss. To determine their effect on productivity, factors like regional labor practices, cultural dynamics, the accessibility of building supplies, and site-specific difficulties need to be empirically investigated. In conclusion, both generally and in the context of Bangladesh, productivity loss in pile construction is a significant concern. A lack of empirical studies that specifically address pile construction in Bangladesh exists despite the fact that international studies have offered valuable data. To comprehend the particular difficulties and establish practical ways to increase productivity in the Bangladeshi construction industry, it is essential to close this gap.

2. Data Collection and Analysis

2.1. Research Framework

According to the study's mechanism, the research was centered on issues with the productivity inadequacies of pile construction projects in Bangladesh. The parameters influencing the productivity of pile construction projects in Bangladesh are then identified. These statistics were obtained after obtaining from multiple projects in Bangladesh. We may look for the baseline value of the productivity loss in pile construction using this data. The baseline is used to assess how accurately pile construction output can be predicted. The 1st phase of this section is factor analysis, which yields a macro impact factor for the productivity of pile construction projects.

The analysis of the data comes next. Data from the first phase are statistically analyzed and described at the outset. To convert qualitative data into quantitative data, various factors and data were set up. This procedure was carried out as part of the data standardization process, in which all data are stated as a 0 if a factor does not occur during working hours and 1 if it does. The data are then transformed into a CSV file and added to the data processor in order to meet the model's requirements.

The third stage involves applying the support vector regression approach to generate the model prediction. This stage begins with loading a converted CSV file into R and selecting syntax as the classifier. Regression, more specifically Support Vector Regression, was used during the development of the model. Setting the parameters that will impact the model's accuracy is the most crucial step at this point. The parameters can be made up of x and y parameters, where y stands for the kernel. Root Mean Square Error was used in the validation test to examine test accuracy (error rate) and the degree to which the actual value and anticipated value correlated with one another. By lowering the factors, the process is repeated from the first step if the accuracy value is higher than the minimal value. The final phase continues until the greatest accuracy figure is determined to validate the suggested model [27] (**Figure 1**).

2.2. Data Analysis

2.2.1. Overview Data

110 data points from finished construction projects completed between 2018 and 2021 were used in the study. All of the projects are construction-related and connect to the goal of this research in one way or another. The comparison establishes pile construction productivity as a macro impact element in Bangladesh. The data must meet the following requirements (**Table 1**).

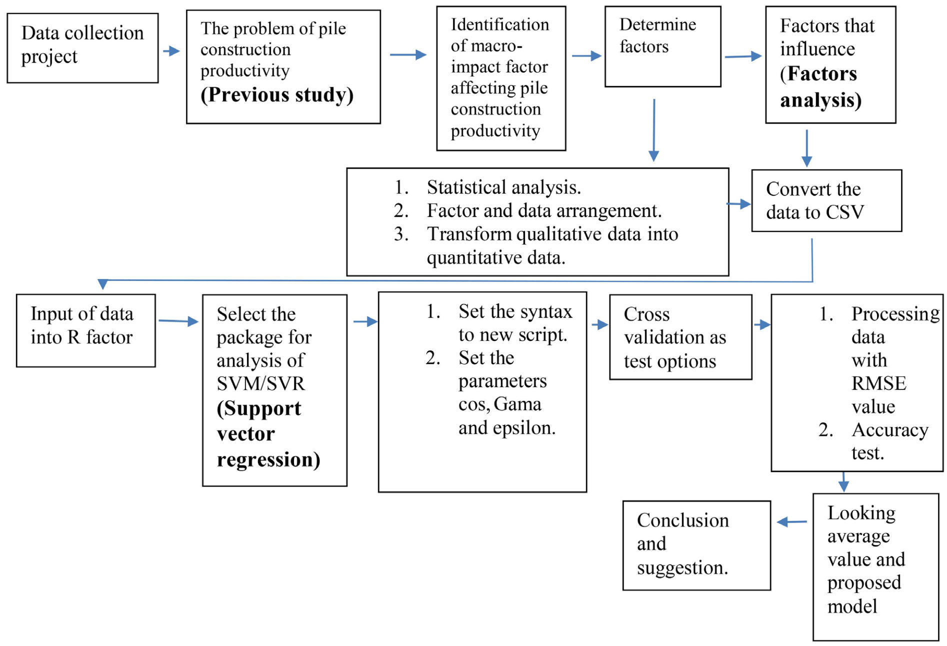

Figure 1. Research procedure.

Table 1. Location characteristics in Bangladesh.

Characteristic	LOCATION				
	DHAKA	SYLHET	KHULNA	NARAYANGANJ	GAZI PUR
SOIL CONDITTION	Bad soil condition/peatland	Clay + sand (mud/silt soil)	Subgrade soil/rock soil	Clay	Clay + sand + gravel
TYPE OF PILE/foundation	Raft foundation	Pre-stressed Precast piles Anchor foundation	Bored Pile (cast in situ)	Pre-stressed/precast piles micro piling or helical piling	Pre-stressed/pre cast piles + bored pile Anchor foundation
Size of the Project (average 864 m^2 – 1548 m^2)	Grade 7 Project of State Minister for State Owned Enterprises > 50 billion				

2.2.2. Project Characteristics

This study used 110 projects from state-owned projects, with grade 7 building (highest grade). The projects' areas ranged from 765 m^2 to 1438 m^2 (Table 2).

The information in the table above is an example from a 110 projects from state-owned projects that took place from 2018 to 2021. According to the factor table, the number 0 denotes obstacle that was on site throughout the specified dates, whereas 1 denotes a lack of obstacle.

For predicting the productivity of pile construction, it's essential to take site characteristics into account. Conditions, environmental conditions, and the location of the project site are examples of sub-factors that contribute to making up the location characteristic [28] (Figure 2).

Table 2. Sample data collected.

No.	Date	Pile Depth	Number of Pile Finish/day	Total Dept.	Work Hour/day	Equipment Sheet	Total Work Hour of Equipment	Daily Productivity	Factor				
		m	qty	m	hour	qty	hour	m/hour	Env.	Equip.	Labor	Material	Manage
		1	2	3 = 1 × 2	4	5	6 = 4 × 5	7 = 3/(4*5)					
1	10/11/2021	13	6	78	12	4	48	1.63	0	0	1	0	0
2	10/12/2021	12	5	60	14	3	42	1.43	1	0	0	1	1
3	10/13/2021	14	5	70	13	3	39	1.79	0	0	0	0	0
4	10/14/2021	12	6	72	15	2	30	2.4	0	0	1	0	0
5	10/15/2021	14	4	56	10	2	20	2.8	1	0	0	1	0
6	10/16/2021	14	3	42	10	2	20	2.1	0	0	0	0	0
7	10/17/2021	14	5	70	11	4	44	1.59	0	1	0	0	0
8	10/18/2021	13	6	78	15	3	45	1.73	0	0	1	0	0
9	10/19/2021	12	8	96	18	3	54	1.78	0	0	0	0	0
10	10/20/2021	12	6	72	15	3	45	1.6	1	0	1	0	0
11	10/21/2021	13	4	52	18	3	54	0.96	0	0	0	0	0
12	10/22/2021	11	4	44	12	3	36	1.22	0	0	1	0	0
13	10/23/2021	11	3	33	10	3	30	1.1	0	0	0	1	0
14	10/24/2021	10	3	30	14	2	28	1.07	0	1	0	0	0
15	10/25/2021	13	3	39	11	3	33	1.18	0	0	1	0	0
16	10/26/2021	14	4	56	15	3	45	1.24	1	0	0	0	0
17	10/27/2021	14	4	56	16	4	64	0.88	0	0	1	0	0
18	10/28/2021	15	4	60	11	4	44	1.36	0		0	1	0
19	10/29/2021	12	3	36	15	4	60	0.6	0	1	0	0	0
20	10/30/2021	13	2	26	13	2	26	1	0	0	1	0	1
21	10/31/2021	12	4	48	15	3	45	1.07	1	0	0	0	0
22	11/1/2021	14	3	42	18	3	54	0.78	0	0	0	0	0
23	11/2/2021	13	3	39	15	3	45	0.87	0	0	1	0	0
24	11/3/2021	12	3	36	10	3	30	1.2	0	0	0	1	0
25	11/4/2021	14	4	56	14	2	28	2	0	1	0	0	0
26	11/5/2021	13	3	39	16	3	48	0.81	0	0	1	0	0
27	11/6/2021	12	4	48	15	3	45	1.07	1	0	0	0	0
28	11/7/2021	15	6	90	17	4	68	1.32	0	1	0	0	0
29	11/8/2021	12	4	48	16	4	64	0.75	0	0	0	1	0
30	11/9/2021	14	5	70	15	4	60	1.17	0	0	1	0	0
31	11/10/2021	12	2	24	10	2	20	1.2	0	0	1	0	1
32	11/11/2021	12	3	36	10	3	30	1.2	1	0	0	0	1
33	11/12/2021	12	7	84	16	3	48	1.75	0	0	1	0	0
Summary			139				1392		7	5	13	6	4

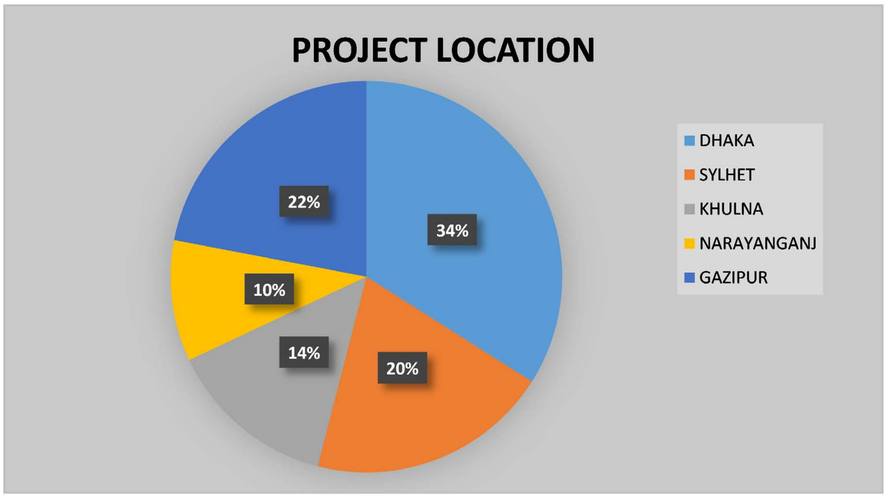

Figure 2. Project location chart.

In Bangladesh, traditional materials like concrete and steel are usually used as piles in construction projects. Because each form of foundation has a unique characteristic, they each have a differed impact on project productivity. **Figure 3**, **Figure 4** detail the different foundation types in each of Bangladesh's cities.

In summary, 19 elements are chosen and divided into 5 groups according to their characteristics, namely: labor, management, environmental, material, and equipment, as shown in **Table 3**, based on the previous research and data [28].

2.3. Factor Analysis

Factor extraction is the analysis method used in this study [29]. Finding the least amount of factors that can be utilized to represent the relationships between the set of variables most accurately is known as factor extraction. To establish which factors are less likely to have an impact on the accuracy of project pile construction productivity, the insignificant factors will be identified and assessed. The information was gathered from construction projects located all around Bangladesh. SPSS software was used to do a factor analysis on the factors that were obtained. Data from the project is inputted to start this process [30] (**Table 4**, **Table 5**).

Depending on the sites soil conditions, several projects with the same function and attributes might use a different foundation type. Building coverage ratio does not accurately reflect the requirements for all projects as the ground floor area is standardized while each project's floors differ. However, in this scenario, almost all of the locations are in easily accessible urban areas, making geography a negligible concern. This is because Bangladeshi contractors will almost certainly choose concrete as the structural material for all types of buildings.

2.4. Macro Impact Factors for Pile Construction Productivity

The value of the model coefficient multiplied by the binary number of factors that happened on each study average day from the first day until the 40th day is

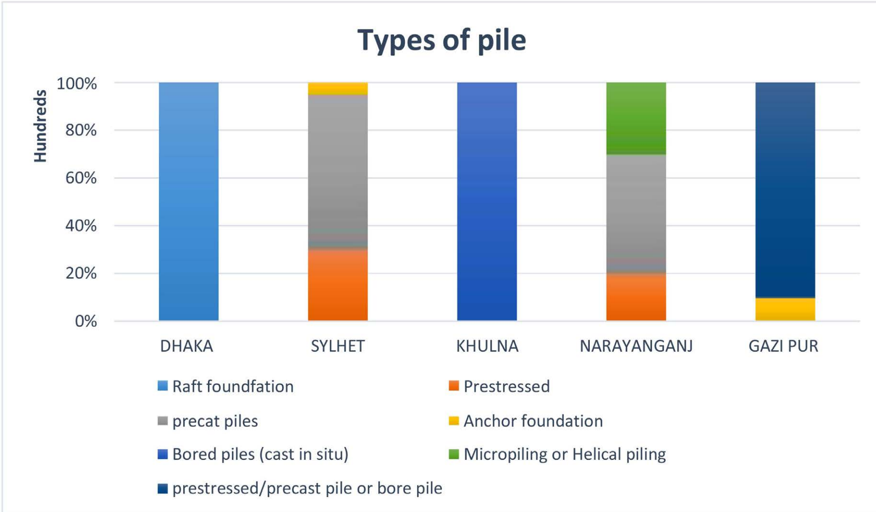

Figure 3. Type of pile chart.

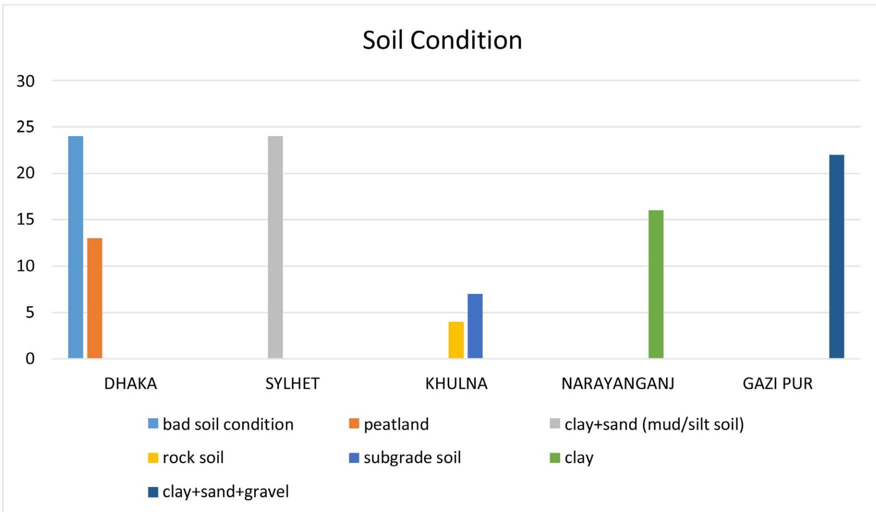

Figure 4. Soil condition chart.

Table 3. Impact factors affecting productivity.

Group	Factors
Labor	Lack of labor skills
	Increase of laborer age
	Labor absenteeism
	Lack of training
	Labor personal problem
Management	Poor site management
	Poor communication
	Misunderstanding between labor and supervisor
	Lack of periodic meeting with labors

Continued

Management	Quality inspection delay Weather changes Project location
Environmental	Working with confined place Large project size
Material	Material shortage Unsuitable material storage location Low quality raw materials
Equipment	Old and inefficient equipment Tools and equipment shortages

Table 4. Macro impact factors input data sample.

Project Data	Impact Factor					Pile Construction Productivity	Total Factor
	Env	Equip	Labor	Material	Management		
1	7	10	14	5	11	26	47
2	6	9	10	6	9	21	40
3	5	8	8	7	8	19	36
4	7	7	9	7	10	20	40
5	14	16	20	15	18	41	83
6	16	8	20	19	12	30	75
7	16	6	20	17	12	28	71
8	16	6	20	17	12	28	71
9	16	8	23	20	11	31	78
10	11	10	19	14	7	26	61
11	11	10	18	13	7	26	59
12	12	6	11	16	10	21	55

Table 5. Demonstrates a data sample that was inserted into the SPSS program me to determine the correlation between 12 of the 110 components.

		Environment	Equipment	Labor	Material	Management
Environment	Pearson Correlation	1	0.382**	0.807**	0.896**	0.556**
	Sig. (1-tailed)		0	0	0	0
	N	110	110	110	110	110
Equipment	Pearson Correlation	0.382**	1	0.467**	0.289**	0.624**
	Sig. (1-tailed)	0		0	00.001	0
	N	110	110	110	110	110

Continued

Labor	Pearson Correlation	0.807**	0.467**	1	0.779**	0.555**
	Sig. (1-tailed)	0	0		0	0
	N	110	110	110	110	110
Material	Pearson Correlation	0.896**	0.289**	0.779**	1	0.483**
	Sig. (1-tailed)	0	00.001	0		0
	N	110	110	110	110	110
Management	Pearson Correlation	0.556**	0.624**	0.555**	0.483**	1
	Sig. (1-tailed)	0	0	0	0	
	N	110	110	110	110	110
Environment	Pearson Correlation	1	0.382**	0.807**	0.896**	0.556**
	Sig. (1-tailed)		0	0	0	0
	N	110	110	110	110	110
Equipment	Pearson Correlation	0.382**	1	0.467**	0.289**	0.624**
	Sig. (1-tailed)	0		0	00.001	0
	N	110	110	110	110	110
Labor	Pearson Correlation	0.807**	0.467**	1	0.779**	0.555**
	Sig. (1-tailed)	0	0		0	0
	N	110	110	110	110	110
Material	Pearson Correlation	0.896**	0.289**	0.779**	1	0.483**
	Sig. (1-tailed)	0	00.001	0		0
	N	110	110	110	110	110
Management	Pearson Correlation	0.556**	0.624**	0.555**	0.483**	1
	Sig. (1-tailed)	0	0	0	0	
	N	110	110	110	110	110

**Correlation is significant at the 0.01 level (1-tailed).

Correlations

			Environment	Equipment	Labor	Material	Management
Kendall's tau_b	Environment	Correlation Coefficient	1	0.285**	0.626**	0.754**	0.369**
		Sig. (1-tailed)	.	0	0	0	0
		N	110	110	110	110	110
	Equipment	Correlation Coefficient	0.285**	1	0.320**	0.190**	0.048
		Sig. (1-tailed)	0	.	0	0.004	0.262
		N	110	110	110	110	110

Continued

Kendall's tau_b	Labor	Correlation Coefficient	0.626**	0.320**	1	0.630**	0.141*
		Sig. (1-tailed)	0	0	.	0	0.026
		N	110	110	110	110	110
	Material	Correlation Coefficient	0.754**	0.190**	0.630**	1	0.242**
		Sig. (1-tailed)	0	0.004	0	.	0
		N	110	110	110	110	110
	Management	Correlation Coefficient	0.369**	0.048	0.141*	0.242**	1
		Sig. (1-tailed)	0	0.262	0.026	0	.
		N	110	110	110	110	110
Spearman's rho	Environment	Correlation Coefficient	1	0.362**	0.771**	0.882**	0.488**
		Sig. (1-tailed)	.	0	0	0	0
		N	110	110	110	110	110
	Equipment	Correlation Coefficient	0.362**	1	0.393**	0.228**	0.078
		Sig. (1-tailed)	0	.	0	0.008	0.208
		N	110	110	110	110	110
	Labor	Correlation Coefficient	0.771**	0.393**	1	0.762**	0.254**
		Sig. (1-tailed)	0	0	.	0	0.004
		N	110	110	110	110	110
	Material	Correlation Coefficient	0.882**	0.228**	0.762**	1	0.402**
		Sig. (1-tailed)	0	0.008	0	.	0
		N	110	110	110	110	110
	Management	Correlation Coefficient	0.488**	0.078	0.254**	0.402**	1
		Sig. (1-tailed)	0	0.208	0.004	0	.
		N	110	110	110	110	110

**Correlation is significant at the 0.01 level (1-tailed). *Correlation is significant at the 0.05 level (1-tailed).

Assumption 2: KMO must be > 0.5 (satisfied)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.780
Bartlett's Test of Sphericity	Approx. Chi-Square	397.197
	df	10
	Sig.	0.000

the measure of productivity loss. Work hours lost refers to the amount of time spent working that is lost due to events that happen during the day [31] (**Table 6**, **Table 7**).

The next stage is to calculate the amount of productivity loss after calculating the model coefficient using the SPSS programmed based on the earlier research [32]. This table displays anticipated loss productivity, which is the amount of loss productivity multiplied by the model coefficient, when a factor occurred. Additionally, work is a value that describes the effectiveness of work hours when disruptive factors happened, multiplying the amount of productivity loss by the number of hours worked.

Working hours multiplied by productivity loss and then divided by productivity at baseline, show the value of work hours lost [33]. **Table 8** shows the calculations for the value of lost output and work hours from 110 projects, and **Figure 5** shows the percentage.

Out of 11.82490 hours, 175.601 hours were lost working hours. Equipment was the element that affected productivity the most because it was likely on some of the working days to have some damaged equipment, which resulted in idle time and significantly decreased project productivity [34].

The second element is labor, as they frequently took breaks outside of break times, increasing idle time and lowering productivity. Researchers advise the contractor to establish a stricter regulation with a more obvious punishment to reduce idle time and lost work hours, improve productivity, and ensure on-time project completion.

3. Model Development

A machine learning technique called Support Vector Regression (SVR) extends the idea of Support Vector Machines (SVM) to carry out regression tasks [35]. The goal of SVR is to create a model that, given a collection of input features, can forecast continuous output values.

3.1. Input Selection

- Identify the problem: Choose the problem that you wish to use SVR to address. Any continuous variable prediction problem, such as forecasting stock prices or home prices, could be involved.
- Specify the input attributes: Pick the relevant features that are most likely to be related to the target variable. These characteristics, which may be numerical or categorical, should to offer useful data for forecasting [36].

3.2. Data Collection

- Collect relevant information: Create a dataset that consists of the predicted variable (the target variable) and the appropriate input characteristics. A broad range of potential input values and target variable variations should be covered by the dataset, ideally.

Table 6. Predictions sample model coefficient of each factors.

Total Work Hours (hour)	Factor Affecting Pile Productivity					Loss of Productivity (m/hour)				
						Env. (0.11)	Equip. (0.89)	Labor (0.51)	Material (0.09)	Manage (0.77)
	Env.	Equip.	Labor	Material	Manage					
32	0	0	0	0	1	0	0	0	0	0.77
22	1	0	1	0	0	0.11	0	0.51	0	0
0	0	0	0	0	0	0	0	0	0	0
68	0	0	1	1	0	0	0	0.51	0.09	0
42	0	1	1	0	0	0	0.89	0.51	0	0
45	0	1	0	0	0	0	0.89	0	0	0
48	1	1	0	0	0	0.11	0.89	0	0	0
8	0	0	0	0	1	0	0	0	0	0.77
SUMMARY										
265	2	3	3	1	2	0.22	2.67	1.53	0.09	1.54

Table 7. Predictions findings sample.

Work Hours Lost (hour)				
Environment	Equipment	Labor	Material	Management
0	0	0	0	4.47
0.44	0	2.04	0	0
0	0	0	0	0
0	0	6.30	1.11	0
0	6.79	3.89	0	0
0	7.27	0	0	0
0.96	7.76	0	0	0
0	0	0	0	1.12
SUMMARY				
1.40	21.82	12.23	1.11	5.59

Table 8. Lost working hour from 110 project caused by macro impact factors.

Factor	Lost Working Hours
Equipment	7.82807
Labor	2.42275
Management	1.57414
Total Work Lost Hour	11.82490
Total Workday (Hour)	175.601

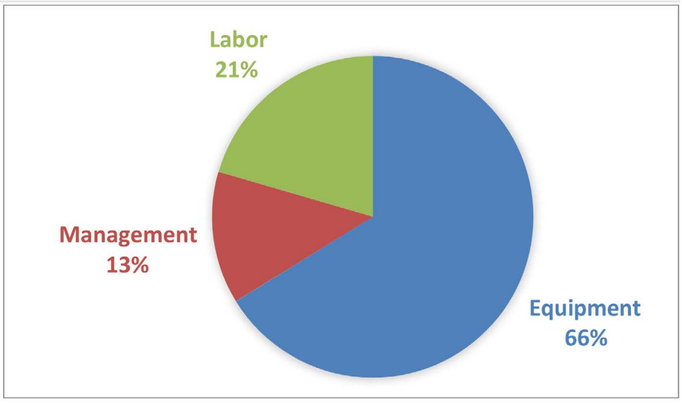

Figure 5. Macro impact factor (Cause of Productivity Loss).

- Ensure high-quality data: Deal with missing values, outliers, and inconsistencies to tidy up the dataset. Depending on the data's qualities, preprocessing techniques like data normalization or standardization may also be used [37].

3.3. Data Preprocessing

- Split the data: Create an initial set of data and a test set by dividing the dataset into two halves. The SVR model is trained using the training set, and its performance is assessed using the test set [38].
- Feature scaling: To ensure that the input features are on a similar scale, normalize or standardize them. The SVR model's performance and convergence can be enhanced via scaling [38].

3.4. SVR Model Training

- Kernel selection: Pick a kernel function that works well with the SVR model. The linear, polynomial, radial basis function (RBF), and sigmoid kernel functions are frequently used. The SVR model looks for the best-fitting hyperplane by transforming the input characteristics into a higher-dimensional space, which is defined by the kernel function.
- Model training: The SVR model is trained using the training set. The regularization parameter (C) and kernel-specific parameters (such as gamma for the RBF kernel) are among the model parameters that must be optimized throughout the training phase.
- Hyper parameter tuning: Use grid search or cross-validation to determine the best settings for the model's hyper parameters. This stage tries to enhance the generalization of the model and avoid overfitting [39].

3.5. Model Evaluation

- Predictions: Use the test set as input for the trained SVR model to forecast values for the target variable.
- Metrics for measuring model performance include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and

coefficient of determination (R-squared). These metrics express the precision and accuracy of the predictions made by the SVR model [40].

- Model refinement: If the model's performance is unsatisfactory, repeat the training and tuning procedures. You may also need to make changes to the hyper parameters or the feature selection.
- Excel data is transformed to a CSV file for the demonstration, which is then entered into the program using the syntax for calling the data and the SVM can be executed. (SVR part of SVM, which is a tool to predict the parameter of SVR). RMSE values are the average value of this error and correlation, according to the modelling findings. If a model has a high correlation value and a low RMSE value, it can be considered to be excellent. The plot clearly shows that there is a high productivity number that differs greatly from the other. The prediction outcome does, however, follow a trend, so the correlation has remained very strong. The three SVR factors in that model are cos, gamma, and epsilon. Using the y formula, each project's statistics can be predicted. In the graph, the project's time is represented by x, and the y-axis represents the value of output loss. The prediction's overall outcomes actually have a high correlation value, so it is appropriate to forecast the subsequent time. Future programmers could incorporate current parameters and elements that influence the outcomes of predictions [40].

3.6. Arranging the Datasets

The normalized datasets for a particular modelling construct were organized using an appropriate random selection basis. Because the data is divided into nominal factors and quantitative factors, standardization is required within the updated data. Nominal variables, like the location's type, are entered into the urban as 0 or 1 for a sub-urban. **Table 9** describes the other nominal variables [41].

The project's size, pile depth, number of completed piles, and equipment quantity are just a few examples of the characteristics that use normalized numbers. These attributes are converted to nominal within a nominal factor of 0 to 1 (**Table 10**).

Because the unstandardized data consists of both qualitative and quantitative data, a data normalization process involving 8 variables is necessary in order to input the data into the SVR model. **Table 11** and **Table 12**, which show the data before and after normalization, respectively, provide an overview of the data normalization procedure.

In order to determine the greatest correlation between data classes after categorizing the data, it is possible to insert the converted data into an SVR model using a 10-fold cross validation model.

The results of the training and testing data without normalization are shown in **Table 13**'s first calculation, which has a large Mean Square Error of 57.24 but still has an acceptable Squared Correlation Value of 0.875. The results of the training and testing data with normalization are shown in the second

Table 9. Inputs and the corresponding labels for the model.

Attribute	Label	Explanation	
Type of soil condition	0	Bad Soil Condition	These labels using normalized number, divide by total label each attributes, and converted to normal within a factor of normal of 0 to 1
	0.14	Peatland	
	0.29	Clay + Sand (mud/silt soil)	
	0.43	Rock Soil	
	0.57	Subgrade Soil	
	0.71	Clay	
	0.86	Clay + Sand + Gravel	
Size of the project Pile depth Number of pile finish Number of equipment	These attributes use normalized number, then converted to nominal within a factor of nominal 0 to 1		

Table 10. Examples of normalized nominal numbers ranging from 0 to 1 are given.

Pile Depth	Number of pile	Size of project	Number of equipment	Pile Depth	Number of pile	Size of project	Number of equipment
26	5	130	4	0.83	0.25	0.43	1
26	6	156	3	0.83	0.5	0.67	0.5
26	5	130	3	0.83	0.25	0.43	0.5
24	5	120	2	0.5	0.25	0.33	0
24	6	144	2	0.5	0.5	0.56	0
24	6	144	2	0.5	0.5	0.56	0
23	5	115	4	0.33	0.25	0.29	1
24	5	120	3	0.5	0.25	0.33	0.5
24	6	144	3	0.5	0.5	0.56	0.5
26	5	130	3	0.83	0.25	0.43	0.5
26	5	130	3	0.83	0.25	0.43	0.5
27	5	135	3	1	0.25	0.47	0.5
27	6	162	3	1	0.5	0.72	0.5
22	4	88	2	0.17	0	0.04	0
24	5	120	3	0.5	0.25	0.33	0.5
23	4	92	3	0.33	0	0.07	0.5
22	5	110	4	0.17	0.25	0.24	1
22	4	88	4	0.17	0	0.04	1
25	5	125	4	0.67	0.25	0.38	1
25	5	125	2	0.67	0.25	0.38	0

Continued

21	4	84	3	0	0	0	0.5
21	6	126	3	0	0.5	0.39	0.5
22	5	110	3	0.17	0.25	0.24	0.5
24	5	120	4	0.5	0.25	0.33	1
24	8	192	4	0.5	1	1	1
25	5	125	4	0.67	0.25	0.38	1
23	5	115	3	0.33	0.25	0.29	0.5
24	4	96	3	0.5	0	0.11	0.5
22	5	110	3	0.17	0.25	0.24	0.5
21	5	105	3	0	0.25	0.19	0.5
23	4	92	4	0.33	0	0.07	1
24	6	144	4	0.5	0.5	0.56	1
25	5	125	4	0.67	0.25	0.38	1
26	5	130	3	0.83	0.25	0.43	0.5
24	5	120	3	0.5	0.25	0.33	0.5

Table 11. Sample data input before normalization.

Project no.	Pile Depth	Number of pile	Size of Project	Number of Equipment	Location	Soil condition	Type of pile	City
52	13	139	1786	3.03	1	0	0	0
102	23	223	5163	3.14	0	3	3	1
99	21	246	5052	3.1	0	1	1	2
98	21	244	5035	3.1	0	1	1	2
90	21	266	5428	3.1	0	1	1	2
70	23	227	5281	3.06	0	3	3	3
69	21	262	5352	3.1	0	1	1	2
64	22	215	4672	3.06	0	2	2	3
59	21	229	5021	3.03	0	1	1	0
58	22	214	4651	3.06	0	2	2	3
57	24	237	5516	3.14	0	4	4	1
38	21	230	4713	3.1	0	1	1	2
36	24	232	5401	3.14	0	4	4	1
26	32	210	6651	3.06	0	5	5	3
22	21	260	5357	3.1	0	1	1	2
16	24	213	5112	3.29	0	4	4	4
14	22	206	4480	3.06	0	2	2	3
13	22	223	4902	2.95	0	2	2	3
12	21	236	4843	3.1	0	1	1	2
11	13	234	3000	3.14	1	0	0	1
10	33	224	7376	3.14	0	6	0	1

Table 12. Sample data input after normalization.

Project no.	Pile Depth	Number Of pile	Size of Project	Number of Equipment	Location	Soil condition	Type of pile	City
52	0	0.52	0.23	0.08	0.5	0	0	0
102	0.5	0.84	0.7	0.18	0	0.43	0.5	0.2
99	0.38	0.92	0.68	0.14	0	0.14	0.17	0.4
98	0.38	0.92	0.68	0.14	0	0.14	0.17	0.4
90	0.38	1	0.73	0.14	0	0.14	0.17	0.4
70	0.5	0.85	0.71	0.1	0	0.43	0.5	0.6
70	0.5	0.85	0.71	0.1	0	0.43	0.5	0.6
69	0.38	0.98	0.72	0.14	0	0.14	0.17	0.4
64	0.44	0.81	0.63	0.1	0	0.29	0.33	0.6
59	0.38	0.86	0.68	0.08	0	0.14	0.17	0
58	0.44	0.8	0.63	0.1	0	0.29	0.33	0.6
57	0.53	0.89	0.74	0.18	0	0.57	0.67	0.2
38	0.38	0.86	0.63	0.14	0	0.14	0.17	0.4
36	0.53	0.87	0.73	0.18	0	0.57	0.67	0.2
26	0.93	0.79	0.9	0.1	0	0.71	0.83	0.6
22	0.38	0.98	0.72	0.14	0	0.14	0.17	0.4
16	0.53	0.8	0.69	0.32	0	0.57	0.67	0.8
14	0.44	0.77	0.6	0.1	0	0.29	0.33	0.6
13	0.44	0.84	0.66	0	0	0.29	0.33	0.6
12	0.38	0.89	0.65	0.14	0	0.14	0.17	0.4
11	0	0.88	0.4	0.18	0.5	0	0	0.2
10	1	0.84	1	0.18	0	0.86	0	0.2

Table 13. Comparison Result between SVR Model with Normalization and without Normalization.

	Total Mean Squared Error	Squared Correlation Coefficient	Number of Support Vectors		0	1	2	3	4
1	57.24	0.875	22	Cos = 1 Gamma = 0.125 Epsilon = 0.1	7.98	6.57	26.21	18.19	29.78
					32.12	15.96	15.56	37.12	14.09
2	0.011	0.872	22		0.01	0.03	0.00	0.00	0.00
					0.00	0.03	0.02	0.00	0.00

calculation. It produced positive results, having a low Mean Square Error of 0.011 and a high Squared Correlation Value of 0.872.

3.7. Interpretation Prediction Result and Discussion

A SVM model called the SVR Model can be used to forecast productivity over a period of time to observe the model's performance in this research [42]. The RMSE (Root Mean Square Error) was applied. The quality of the generated model increases with decreasing RMSE performances. The best performance or the smallest RMSE from 110 data pile construction productivity was determined by this research. There are many instances of productivity that differs from the others because it has a large margin but also has a large RMSE number (more than 1). Even though the RMSE is high, the correlation value is still high because the predicted outcomes still follow the pattern of the real data. Because the expected results continue to match the pattern of the actual data, correlation stays high. The pattern of the predicted data matches that of the real data, making the model suitable for prediction [42]. The SVR parameters are used in the same model for the entire range of output (1 - 110).

c = 1.

Gamma = 0.125.

Epsilon = 0.1.

Consequently, it can be said that the model is adequate for use in making predictions tools.

Out of 110 projects, 100 projects' data—or 90% of the total—were used to train the network, and the final 10 projects' data—or 10%—were used for testing. The network predicts production rates during training with reduced MSE values and follows the same trend and pattern of target values as shown in **Figure 6**. Because of the high correlation value, the prediction graph in the results with higher RMSE value continues to follow the pattern of the real value graph. The value of productivity loss caused by a factor during construction, which was measured over a 40-day period, is represented by the Y-axis, and the duration is indicated by the X-axis.

As shown in **Figure 7**, productivity rate values predicted during testing also have reduced error values and follow a nearly identical trend and pattern with a small variation at the conclusion.

The MSE of training and testing predicted rates have been determined for training and testing as shown in **Table 14** and **Table 15**. Average values of each project's predicted rates have then been computed. (**Table 16**)

The pattern and correlation between the actual value and the forecast are shown in **Figure 6** and **Figure 7**, which demonstrate the prediction's accuracy. If the model had a high association value and a low MSE value, it would be suitable. In order to conduct further study, it is possible to add impacting factors and existing parameters to the model, which will produce a prediction. Cost, gamma, and epsilon are the three factors that were used for SVR. The error rate can be used to determine success rate, but it is impossible to calculate the error rate because the actual y-axis includes a value of 0 [43].

Response variable (y) and prediction variable made up the research variable. (x). X and Y variables were first grouped in Microsoft Excel for initial data processing. The future/target (y) pile output loss was measured using support vector machine data processing, and 110 data sets were used as input.

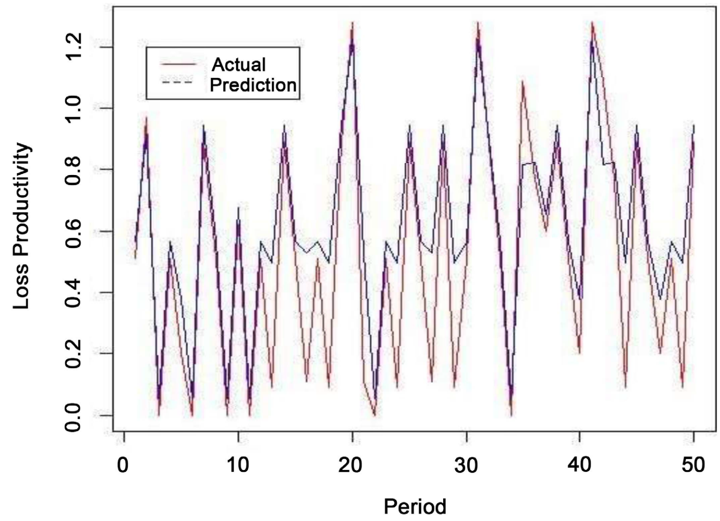

Figure 6. Curve output training error.

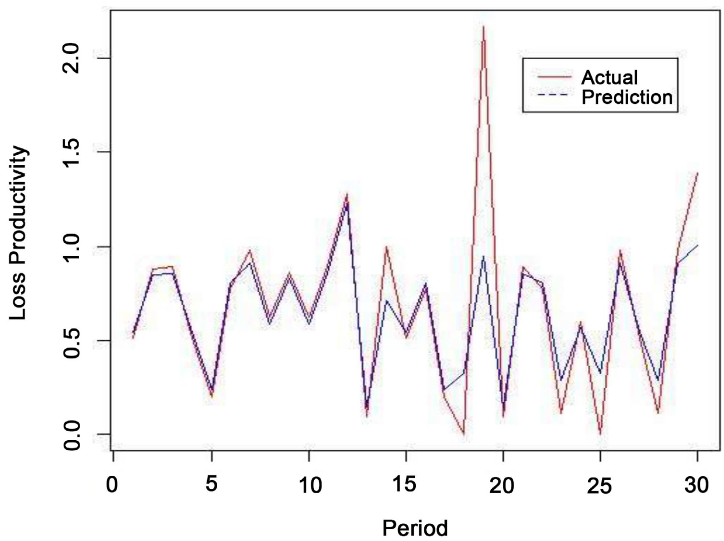

Figure 7. Prediction testing curve result.

Table 14. Model result training data.

Combination 10-fold cross validation with Data Training	Total Mean Squared Error	Squared Correlation Coefficient (Accuracy Rate)
1	0.11	0.68
2	2.06	0.07
3	2.15	0.42
4	2.1	0.41
5	0.06	0.75
6	0.00	0.99
7	0.07	0.73

Continued

8	0.01	0.72
9	0.01	0.73
10	2.17	0.8
AVERAGE	0.87	0.63

Table 15. Model result testing data.

Combination 10-fold cross validation with Data Testing	Total Mean Squared Error	Squared Correlation Coefficient (Accuracy Rate)
1	0.01	0.74
2	0.02	0.83
3	0.01	0.87
4	0.01	0.94
5	0.01	0.91
6	0.01	0.87
7	0.02	0.82
8	0.01	0.92
9	0.01	0.89
10	0.01	0.9
AVERAGE	0.011	0.868

Table 16. Difference result.

	Total Mean Squared Error	Squared Correlation Coefficient (Accuracy Rate)	Note
Combination 10-fold cross-validation with Data Training	0.87	0.63	The model is adequate if it had high correlation value and smaller MSE value
Combination 10-fold cross-validation with Data Testing	0.011	0.868	
Difference	0.859	−0.238	

For parameter setting using SVM algorithm, it is known that productivity loss configuration prediction was by using data input of the previous project for k-fold 10, C (cost) = 1 and kernel type radial. Configuration design to predict the productivity loss for the future was calculated, and the result is:

The best result or smallest Mean Square Error in Table 17 is 0.01 with a Squared Correlation Coefficient of 0.87 and 22.00 support vectors [44]. The SVM algorithm was used in this study's data processing along with data calculation construction, which involved entering training data (10 data combinations), choosing the kernel type, the C (cost) number, and the k-fold. The reason for calculating the SVR parameter is as follows:

1 cost of constraint violation (default: 1). This isthe 'C'-constant of
The regularization term in the Lagrangeformulation
0.125 parameter needed for all types of kernelsexcept linear,
Default: 1/(data dimension), Data dimension: 8 factor
0.1 (Default)

The operating system used for training and forecast is defined by kernel. The choices include sigmoid, radial basis, polynomial, and linear. The used kernel type was radial, with a C (cost) value of 1, and a k-fold number of 10. The testing outcomes, which were performed using various kernel functions and inserting C (cost) and range (k-fold) values chosen based on each data collection, are shown below. After determining k-fold validation, c (cost) and kernel type, smallest MSE (mean square error) were found. The smallest MSE mentioned is the one that served as both an accuracy benchmark and a design to forecast benchmark [45].

The potential input loss that the project may experience is predicted by SVR models in Table 18. The model shows the potential amount of prediction loss. 40 times of looping are used to find the most comparable figure. The prediction itself and the influence of the 8 factors used in this study linked to the effect of pile construction productivity performance itself have the smallest and most repeatable potential values for measuring excellent productivity loss. Euclidean distance is one technique for measuring similarity.

The formula is as follows:

$$d(p,q) = d(q,p) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$
$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

The scenario with the smallest number of Euclidian distances from the model, according to Table 18, is case number 16.

This model can be used to predict the productivity loss of a project in the future, and forecasting using SVR method has the smallest standard error value and the results are close to the original data. Potential loss prediction aims to reduce lost work hours caused by factors occur in the project. This can be seen from the results in Table 19. The potential loss prediction is 0.1855 (equivalent to 18.55%). It intends to raise output in the future.

Table 17. Prediction result recapitulation with 8 factors.

No.	Total Mean Squared Error	Squared Correlation Coefficient (Accuracy Rate)	Number of Support Vectors	Parameter	K = 10 fold				
1	0.01	0.74	16	Cos = 1 Gamma = 0.125 Epsilon = 0.1	0.105 0.001	0.002 0.002	0 0	0.001 0	0 3 0 0
2	0.02	0.83	23		0.13 0.001	0.001 0.006	0.006 0.007	0.022 0.012	0 1 0 1
3	0.01	0.87	22		0.022 0.006	0.001 0.004	0.001 0.005	0.037 0.002	0.01 0 0 4
4	0.01	0.94	21		0.001 0.019	0.005 0.004	0.012 0.001	0.001 0	0 5 0 5
5	0.01	0.91	20		0.001 0.037	0.001 0.004	0.001 0.004	0.009 0.007	0.01 4 0 1
6	0.01	0.87	18		0.005 0.01	0.022 0.004	0.008 0.038	0 0.002	0 1 0.01 0
7	0.02	0.82	23		0.001 0.001	0.006 0.001	0.14 0.006	0.014 0.002	0.01 0 0 1
8	0.01	0.89	20		0.005 0.013	0 0.019	0.006 0.001	0.017 0.008	0 1 0 2

Continued

9	0.01	0.92	23	Cos = 1 Gamma = 0.125 Epsilon = 0.1	0.006 0.007	0.004 0.005	0.004 0.008	0.013 0.007	0 6 0 6
10	0.01	0.9	20		0 0.044	0.001 0.016	0.02 0.001	0.001 0.003	0 4 0 2

Table 18. Sample of prediction potential loss result.

Comparison Data Number	Work Hour Lost in Data Model	Work Hour Lost from Comparison Data	Euclidean Distance
16	76.61	76.65	0.04
53	76.61	76.89	0.28
24	76.61	76.26	0.35
97	76.61	76.18	0.43
60	76.61	76.18	0.43
66	76.61	76.06	0.55
99	76.61	77.76	1.15
4	76.61	77.80	1.20
35	76.61	75.33	1.28
9	76.61	75.24	1.37

Table 19. Recapitulation of potential loss result.

Lost Productivity (hour)	Environment	12.91
	Equipment	66.68
	Labor	58.21
	Material	16.18
	Management	76.65
Total Work Hour Lost		230.65
Overall work hour		1243
Productivity Loss Percentage		0.1855 (18.55%)

The quantity of work created per unit of input or effort is referred to as productivity. Contractors typically experience loss in output, which involves completing work at a slower pace than anticipated. Numerous studies have been conducted on the factors that contribute to productivity loss. Typical factors include acceleration (either positive or negative), unfavorable or unusually severe weather, the cumulative effect of numerous changes and revisions, site or work area access restrictions, site conditions, untimely approvals, and responses to labor market conditions [46].

Acceleration: When work must be completed by contractors more quickly than anticipated, this is referred to as acceleration. This might take place as a result of unanticipated events, project delays, or changes in the timetable. Contractor productivity may suffer if they are required to complete their work more quickly since they may have to use more resources or compromise quality to meet the tighter deadlines.

Unfavorable or abnormally severe weather: The weather can have a big effect on building projects. Weather that is unfavorable, such as severe thunderstorms, snowstorms, or intense heat, can hinder construction efforts and impede progress. Because contractors may need to reschedule work or take extra care to maintain safety and quality, delays brought on by unfavorable weather conditions can lead to lower production.

Cumulative effect of changes and revisions: Throughout the duration of a project's life, modifications and revisions are frequently made. These alterations may be brought on by alterations in the design, demands from the client, or unanticipated problems found during the construction process. Multiple changes taken together can have a disruptive effect on workflow, require more coordination work, and take more time and money to implement. Productivity loss may result from these interruptions.

Restrictions on access to the construction site or work areas: Contractors may encounter difficulties as a result of the sites or the work areas' restricted access. Access restrictions may be necessary for site management, safety reasons, or to coordinate with other ongoing activities. Access restrictions can make it difficult for people to move about and access equipment and materials, which reduces production.

Delayed clearances and answers: Maintaining productivity depends on timely approvals from the appropriate authorities and quick responses to contractor concerns. The construction timetable may be disrupted and progress hampered by delays in receiving required permits, approvals, or answers to questions. Contractors might be forced to wait for decisions, alter their plans, or halt work, all of which could reduce production.

Site conditions: Productivity can be impacted by the environment at the construction site. Contractors may encounter difficulties and have their productivity impacted by elements like uneven terrain, poor soil quality, the presence of hazardous materials, or inadequate infrastructure. It might take more time and money to address the site's problems and put essential mitigation measures in place, which could negatively impact productivity.

Labor market conditions: Changes in the labor market, such as labor shortages or salary changes, can have an impact on the construction industry's productivity. Reduced workforce availability, greater competition for competent workers, and significant delays in hiring and training new employees are all effects of labor shortages. Project timeframes and general productivity may be affected by these variables.

A new perspective for engineers studying the delay causes with productivity loss is provided by the outcome of key activities as it relates to loss in productivity and overall factors incurred. In the building construction industry, effective management should place more emphasis on the correlation between productivity loss and the factors that cause it. Therefore, to represent the effect on productivity loss, real factors causes can be summed up as a loss in productivity problem.

Loss of Productivity by category [46]:

Environment: The test results indicate that 12.91 hours of productivity were lost due to environmental factors. Environmental factors can include adverse weather conditions, noise, vibrations, or other external influences that hinder construction progress.

Equipment: The test results show that 66.68 hours of productivity were lost due to equipment-related issues. Equipment problems can range from breakdowns or malfunctions to inadequate availability or performance, all of which can impact the efficiency of construction activities.

Labor: The test results indicate that 58.21 hours of productivity were lost due to labor-related factors. This could include issues such as labor shortages, skill gaps, absenteeism, or inefficiencies in workforce management.

Material: The test results show that 16.18 hours of productivity were lost due to material-related factors. Material issues could include delays in material delivery, inadequate quality or quantity of materials, or problems with material handling and storage.

Management: The test results indicate that 76.65 hours of productivity were lost due to management-related factors. This may involve issues such as poor planning, ineffective communication, inadequate coordination, or inefficient decision-making processes.

Based on these results, it is evident that productivity loss has occurred across various categories, including environment, equipment, labor, material, and management. The overall productivity loss percentage of 18.55% indicates a significant impact on the efficiency of the construction activities during the tested period. Understanding and addressing the underlying causes of productivity loss can help improve project planning, resource allocation, communication, and management practices to enhance overall productivity in future construction endeavors.

3.8. Limitations and Assumptions of SVR

- SVR makes the assumption that there is a continuous link between the input characteristics and the target variable, which can be illustrated by a hyperplane or non-linear decision boundary.
- SVR makes the assumption that the data is independent and identically dis-

tributed (i.i.d.), which means that there is no interdependence between the observations in the dataset.

- The kernel function and model hyperparameters can have an impact on SVR performance. It can be difficult to choose the right parameters.
- Therefore grid searches or experimentation may be needed.
- Due to the possibility of overfitting, SVR may not perform well on datasets with a lot of features or when the dataset size is minimal.
- SVR can be expensive to compute [47].

4. Conclusions

Because each construction job is unique and because this sector is inherently complex, establishing the dynamic indexes of performance used for each unique work is essential. Most productivity evaluation tools and benchmarking techniques take a comprehensive approach. These techniques use a subset of project performance as their foundation because they don't consider net sources when setting policy and benchmarks. The removal of resource losses from base value determination is its main benefit over other currently used methods. Additional benefits include the introduction of the net baseline productivity index and its comparison with the project's macro productivity, objective-based access to and definition of productivity measurement methods, and more. The framework's true qualities and advantages are also demonstrated when it is fully implemented as the suggested course of action in the circumstances under investigation.

There are several similarities and variations between productivity loss in pile construction especially and productivity loss in other types of construction.

Similarities: Environmental Factors: Adverse weather circumstances, including intense rain or extremely high temperatures, can have an impact on pile construction, just like they can on other building activities. These circumstances may slow down the process, create delays, and reduce productivity.

Factors associated with labor: Pile building necessitates the use of skilled labor for activities like driving piles, digging, and strengthening. Productivity can be impacted by labor-related issues such as labor shortages, skill gaps, or unavailability in both general construction and pile construction.

Differences: Pile construction requires the use of specialized machinery that may not be as common in other types of construction, such as pile drivers, drilling rigs, and cranes. Productivity in pile construction can be significantly impacted by equipment-related variables including failures, insufficient availability, or improper maintenance.

Pile construction sometimes takes place in difficult site circumstances, such as unsteady soil, marshy locations, or crowded metropolitan settings. Dealing with these site-specific difficulties can make pile construction more complicated and may result in further lost productivity.

Material handling: Concrete, reinforcing, and piles are only a few of the materials used in pile construction. Delays or issues related to the delivery, availability, or quality of these materials can impact productivity specifically in pile construction projects.

Planning projects, managing risks, and allocating resources can all be affected by understanding the similarities and variations between productivity loss in pile construction and general construction. It emphasizes the necessity of specialized training in pile construction methods, tools, and material management. Project stakeholders can create focused strategies to reduce risks and increase productivity by recognizing the particular elements specific to pile construction that contribute to productivity loss. This could entail putting in place efficient material management and delivery systems, making sure equipment is properly maintained and available, and taking proactive actions to mitigate weather-related delays.

This study also produced a novel method for creating productivity baselines, which is presented in depth with an emphasis on the macro impact factors influencing pile building productivity. This method's potential and scientific applications are demonstrated by using it experimentally on case studies; it can be applied to the tools, materials, and apparatus.

Future research may focus on gathering changing net baseline output values from various project components and comparing those values to benchmarks offered by formal systems. In subsequent works, it might be essential to assess how this strategy performs and has an impact on the relevant stakeholders, such as the client or governing body. For the 110 project, where the total workday was 175.601 hours, the following details are how we determined the lost productivity and labor hours:

Work hours loss due to equipment factors increase by 7828, 07 hours. Work hours loss due to labor factors increase by 2422, 75 hours.

Work hours loss due to management factors increase by 1574, 14 hours.

The tools used are the single most crucial element when it comes to the general productivity and efficiency of a construction job. Since the aforementioned standards weren't always reliable, only economic variables could be used to generate an approximation. By determining the component that is limiting or anticipating the loss of output, SVR (Support Vector Regression) can be used to forecast it. Everything is governed by rules, including how the site is placed and how the different components interact.

On-site tally sheets have been used to keep track of arbitrary variables like the weather, the availability of supplies and tools, the location of the project, and the specifics of the site. Severity indices have been created in order to allow for the impartial assessment of each element's effects. One of the most important factors affecting the precision of output rate estimations is the regularity with which materials and equipment are made available.

The SVR model has successfully predicted exact values for the production rate using these characteristics. We calculated the percentage error and Mean Square Error (MSE) of the expected output to evaluate the model's accuracy. An SVR model for predicting productivity loss in Bangladeshi pile construction was built using 110 data from the study's assessment and the implementation of 10-fold cross validation. In contrast to their correlations of 0.011 and 0.866, the MSE for training and assessment outputs is 0.87 and 0.63, respectively. The ideal performance (or least Mean Square Error) is 0.01 with 22.00 support vectors, an accuracy rate of 87, 25931%, and a potential output loss of 18.55 percent. According to these findings, the SVR model correctly predicted concrete column output rates with a tolerable degree of error.

In a building project, concentrating on waste reduction and productivity increase techniques may have various advantages. First off, by detecting and eliminating waste, resources may be used more effectively, which reduces costs. Lower project costs can be achieved by cutting out wasteful stages, minimizing rework, and maximizing material use. Second, a shorter project timeline and lower overhead expenses are the benefits of increased production. Additionally, greater efficiency raises the standard of work as a whole, resulting in happier clients and perhaps even repeat business or positive recommendations. Finally, by putting productivity improvement techniques into practice, contractors can develop a competitive edge, attracting new customers and landing higher-paying contracts. In the long run, these strategies will help the construction sector be more profitable and successful.

Research Recommendation

The research has produced the best and most accurate forecasts; however, the following areas need to be improved in the following study to produce better results:

More observational data must be used for simulation in order to generate more data for the model's training process, which will lead to predictions with greater precision. According to Furey (2021), the validity of the comparison finding cannot be questioned because, with more data, SVM can be tested in experiments of greater scale.

Using a linear function within a feature space and adding learning bias to the SVM model is necessary for improved prediction.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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