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Original Article

Prediction of Consumables Requirement in PEB Manufacturing Using Probabilistic Grouping and Random Forest Regression

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Abstract - *Within the Pre-Engineered Buildings (PEBs) framework, error-free consumable prediction poses a significant challenge due to the inherent variation in project designs, component types, and fabrication scales. Conventional estimation practices may not be able to capture such complexities, thus leading to inefficiencies, cost overruns, and wastage of excess materials. The current research introduces a data-driven methodology that applies machine learning techniques, especially Random Forest Regression (RFR), to develop a robust predictive model trained on concurrent PEB projects. The total fabrication tonnage of each project is broken down into different amounts of individual components, which are further used as structured inputs for predictive model training. A multi-output forecasting strategy is employed to facilitate concurrent forecasting of multiple consumable needs for similar future projects in a single execution. Probabilistic clustering based on major fabrication consumables and scales is applied to enhance the accuracy and precision of the forecasts produced by the model. Hyperparameters are tuned through GridSearchCV; hence, the exactness and model generalization are improved. The proposed methodology demonstrates significant improvements in forecasting accuracy, facilitating improved resource planning, cost effectiveness, and sustainability in PEB fabrication processes. The results highlight the potential advantages of incorporating machine learning methodologies in construction planning for facilitating more intelligent and scalable decision-making practices.*

Keywords - *Artificial Intelligence (AI), Machine Learning (ML), Consumable prediction, Pre-Engineered Buildings (PEB), Random Forest Regression.*

1. Introduction

The increasing application of Pre-Engineered Buildings (PEBs) in present-day construction is due to their flexibility, rapid assembly processes, and cost-effective benefits. Nonetheless, stakeholders have never been able to make reliable predictions of material consumption, mainly due to inherent variability with respect to project-specific designs, scale of production, and component interdependencies. Conventional estimation methods tend to lack the complexity to address such complexity, thereby leading to inefficiencies in the form of excess inventory, order delays, or inefficient utilization of resources [4, 16]. Most existing studies on material forecasting in construction either focus on bulk cost estimation or generalised material classes, with limited attention to member-specific consumables or stage-wise manufacturing data. Additionally, very few have applied machine learning in the context of PEB fabrication plants, particularly for predicting multiple consumables simultaneously. To address such a problem, the current work employs a novel framework that integrates probabilistic project classification with Random Forest Regression (RFR) to predict the usage of 100+ consumables across multiple fabrication stages and to improve the precision of prediction by training the model on diversified real-time data inputs that deconstruct total project tonnage into individual member quantities from PEB projects. Instead of taking disconnected high-level indicators, input data breaks down total tonnage into individual fabrication elements (utilizing 45+ fabrication members as input), thus allowing the model to understand complex project characteristics and material requirements interdependencies. The process involving multiple inputs from the project leads to a system that allows multi-output prediction, thus creating a more advanced platform for resource management and consumable forecasting [5–7]. In addition to improving operational effectiveness by employing a probabilistic group strategy and incorporating fabrication quantity thresholds, the model also encourages more sustainable building practices through reduced waste and optimal utilization efficiency of resources [8–10]. While previous works have used machine learning for cost forecasting or construction productivity, their models often rely on high-level project indicators rather than detailed fabrication datasets. In contrast, our model is trained on actual member-wise tonnage data, enhancing prediction specificity and real-world applicability [2, 5, 8, 10, 14]. The research further aims to evaluate prediction accuracy across distinct classification sets and to demonstrate how such predictions can enhance material planning, reduce procurement risks, and improve cost-efficiency compared to conventional estimation methods.

2. Literature Review

The advancement of construction methods has always necessitated more precise and reactive means of material planning, especially in industrialised structures such as Pre-Engineered Buildings (PEBs). While these systems are time and modularity-effective, they also come with massive complexity in the aspect of variability in components and tonnage-based fabrication needs. This has brought about a paradigm shift in academic literature from traditional deterministic estimation methods to learning systems that are able to learn from experience [3, 11, 12].

ML usage in manufacturing and construction has gained considerable traction in recent years. Sadatnya et al. (2023) employed ML models to predict construction crew productivity from work reports on a daily basis, enabling enhanced labour planning and scheduling efficiency [1]. Villegas-Ch et al. (2024) combined computer vision with ML to enhance inventory management, demonstrating the benefits of real-time monitoring and automated tracking [15]. In steelmaking, Raju et al. (2022) applied ensemble learning techniques for demand forecasting, with improved predictive accuracy compared to conventional statistical methods [12]. Similarly, Zermane et al. (2024) paired ML and time-series analysis to predict material requirements, which correctly represented temporal consumption patterns [3]. These studies demonstrate the applicability of ML techniques for resolving challenging forecasting issues, establishing a strong precedent for forecasting consumable requirements in PEB fabrication processes.

Although conventional estimation techniques are based on empirical approximations or historical averages, they lack the ability to cope with the dynamic requirements of heterogeneous fabrication scales, component types, and design variations. This limitation has encouraged the application of Machine Learning (ML) models in construction fields to strengthen predictive reliability and operational efficiency. Existing research has supported the viability of ML applications in construction fields like cost estimation, energy consumption modeling, and resource planning. For instance, Mohammed et al. [8] explored the potential of smart prediction technologies to enhance construction productivity, whereas Jeong et al. [4] employed ML in productivity prediction in prefabricated systems, with the benefit of data-driven decision-making in modular construction processes.

For this issue to be addressed, more researchers have utilized Machine Learning (ML) methods that can identify patterns in project historical data and improve predictive precision. Specifically, Random Forest Regression (RFR) has been particularly promising since it can handle large amounts of complex datasets and suppresses the risk of overfitting. Its validity has been published in various application areas in the construction industry, including cost appraisal and resource programming [2, 6, 10, 14]. Rajasekaran [10] emphasized its reliability in manufacturing-based prediction tasks, while Li et al. [6] combined ML and optimizing fabrication process and rescheduling in Industry 4.0 environments, underscoring RFR's role in flexible industrial contexts. Despite its effectiveness, the use of RFR for forecasting consumables at a granular level, especially within PEB fabrication, remains relatively underexplored.

In many of the aforementioned studies, project data is often treated at an aggregate level, focusing on overall cost or schedule trends rather than item-specific material usage. This restricts the applicability of such models in fabrication-driven environments, where the breakdown of material by component and stage is crucial for accuracy and cost control. Additionally, while works like Mateus et al. [7] and Karthick et al. [5] explored energy or steel production forecasting using advanced ML models, they typically do not incorporate probabilistic grouping based on project type or fabrication stage, nor do they enable multi-output predictions for multiple materials simultaneously. Recent research highlights the importance of preprocessing project data before deploying Machine Learning (ML) models. The present study suggests a Random Forest Regression model trained on real-time datasets collected from a PEB manufacturing plant to explore this challenge. Input features of the model are collected through deciding the total fabrication tonnage into member-level quantities (e.g., rafters, columns, and joists), while outputs are in the form of different types of consumable materials consumed along the length of the production line.

With the incorporation of probabilistic grouping of projects based on structural configuration and fabrication scale, the model attempts to offer more tailored and accurate forecasts than conventional estimation methods. Projects of a similar nature are clustered around principal components or the fabrication level, thus enhancing the model's overall performance. [12, 13] Methods such as GridSearchCV are used to enhance the effectiveness of the model [8, 9]. These methods not only enhance the accuracy of predictions but also enable waste minimization, cost-effectiveness, and sustainability in Pre-Engineered Building (PEB) construction.

3. Methodology

This research aims to build Machine Learning (ML) models that are meant to predict the use of different materials in the Pre-Engineered Building (PEB) component-manufacturing facility. The models are meant to be built to maximise resource use through the analysis of past data obtained from previous PEB manufacturing operations. Traditional approaches to estimating consumables during PEB fabrication rely on typical consumption rates, rule-of-thumb estimates, or past averages. Easy to use, these approaches tend to ignore project-specific parameters like changes in component weights, fabrication order, or member geometry. Consequently, they yield generic estimates that do not accurately account for real-time material needs, particularly for custom-fabricated or complex projects.

The machine learning approach eliminates these limitations by directly learning from past project records, thus decomposing total fabrication tonnage into granular member-wise inputs. In addition, with the utilization of probabilistic project clustering based on structural configuration, the model accommodates customized, multi-output predictions for 100+ consumables. This data-driven methodology not only enhances forecasting accuracy but also minimizes reliance on subjective judgment, enabling planning to be more scalable and repeatable across project types. 70+ datasets were obtained from a PEB manufacturing company that possessed its own independent fabrication plant. The datasets contain data regarding more than 45 fabricated structural components, involving the utilisation of more than 100 types of consumables for PEB jobs. Figure 1 shows the workflow for handling and preparing data.

The first phase involved a cleansing procedure for the data, in which records deemed incomplete datasets, specifically those missing information on quantities of components or associated with active projects, were removed. Such exclusions are largely due to human error in reporting or activity performed on-site. Because this research is concerned with operations only within the factory, such anomalies lay outside the ambit of the study; the datasets were subsequently divided by the sum of the weights of components produced per project, in Metric Tonnes (MT).

For consistency and analytical precision, only projects between 30 MT and 110 MT weights were kept for subsequent analysis. Structurally ranked according to importance, elements such as rafters and columns are considered critical elements of the PEB project. Depending on their occurrence, the data sets were classified into: Group P1: Projects that include both column and rafter elements. Group P2: Projects including only a column or a rafter. To further refine the analysis, the fabrication components were clustered into three configuration levels: Category C1: Projects that consist entirely of rafters and columns. Category C2: Includes C1, with additional information such as eave columns, joists, portal beams, portal columns, and canopy rafters. Category C3: Extends C2 to include crane beams and jack beams. Every group of data was divided into a configuration type based on the proportion of these key elements in the overall project: 1. More than 75% of C1 elements, 2. More than 80% of C2 elements, 3. More than 85% of C3 elements are in both P1 and P2 groupings. It was found that, following all data refinement stages (as depicted in Figure 1), the sizes of the datasets remained equivalent across the paired configurations: P1C1 and P2C1, P1C2 and P2C2, and P1C3 and P2C3. Therefore, the subsequent machine learning modelling was conducted on these three harmonized sets of datasets to enable comparative analysis on a balanced basis across the project types and component configurations.

The resultant group of project datasets under each paired set of classification after the completion of preprocessing is assessed. Altogether, 29 components, such as columns, rafters, portal beams, and other PEB members, seem to have been fabricated. Among these 29 members, 15 components are found to be in all 3 sets of classification. The total tonnage is broken into quantities of each member; therefore, the training of machine learning models becomes even more precise. Multiple user input values will be given, and a list of multi-variable consumables quantities will be the output. Likely, the similarities between all 3 sets were studied and are as follows. More than 100+ consumables are being used in the fabrication process. Among these, 87 consumables are commonly found to be used in all 3 sets of classification. Whereas set 1 - P1C1 vs P2C1 comprises the same 87 consumables, and the other 2 sets (P1C2 vs P2C2 and P1C3 vs P2C3) consist of 91 and 101 consumables, respectively. From these many consumables, about 37.5%, 26.92% and 25% of consumables are found to be the most majorly used in the maximum datasets in all the 3 sets, respectively.

Fig. 1 Data preprocessing of PEB projects

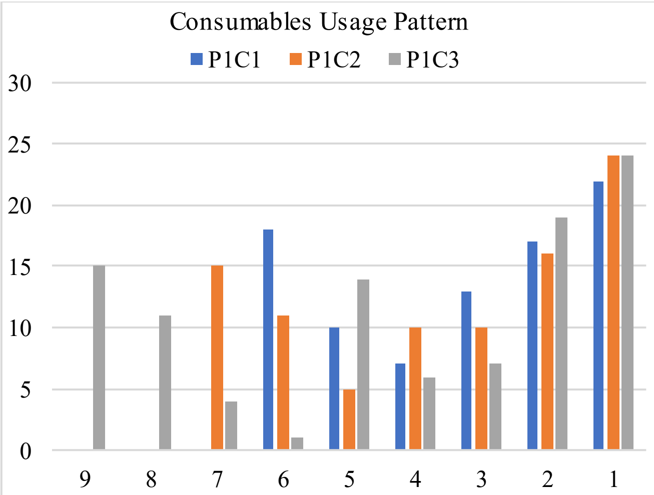


Fig. 2 Consumables usage pattern in varied projects

Figure 2 presents the utilization pattern of consumables in PEB projects under all 3 categories (P1C1, P1C2 and P1C3). For example, under category P1C3, 15 various consumables are utilized in all 9 projects. Establishing a base, wherein consumables utilized in (>= 5) projects from the 3 classifications are then categorized as significantly utilized consumables. Those utilized in (>= =) to 3 and <= 5 of the PEB datasets are referred to as moderately utilized consumables. In the same way, consumables utilized in (< 3) projects are referred to as rarely utilized consumables, as stated in Figure 2.

A small subset of uncommon consumables, 4 from P1C2 and 14 from P1C3, were observed to be utilized only in either P1C3 or P1C2. Surprisingly, these consumables not being utilized come in the range of less significant or rarely used consumables. Notably, it doesn't reflect any significant influence on the datasets. Figure 2 also reflects around 55.17%, 56.04%, and 57.43% of combining the most important and moderately utilized consumables in P1 C1, P1 C2 and P1 C3, respectively.

4. Development and Evaluation of the Machine Learning Model

Random Forest Regression was used for prediction modelling in this research due to its effectiveness in handling datasets with a large number of input variables and its inherent capacity to handle overfitting. Its inherent ensemble property makes Random Forest particularly well-suited for prediction modelling in industrial applications, e.g., manufacturing of PEB components. The model was hyperparameter-tuned to achieve its highest prediction accuracy, and cross-validation techniques were used to ensure that it generalized well on new data.

The Random Forest Regression (RFR) model was incorporated into Python's scikit-learn library. The input features consisted of the total quantity (tonnage) of each fabrication member per project, while the output was the corresponding usage of over 100 consumables. The dataset was divided at random, with 80% chosen to train and the remaining 20% kept for testing. Hyperparameter tuning was performed using a grid search combined with 5-fold cross-validation, focusing on frameworks such as the number of estimators (n_estimators), the maximum tree depth (max_depth), and the minimum number of samples required to split a node (min_samples_split). The RFR model was evaluated across all three classification pairs using R^2, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

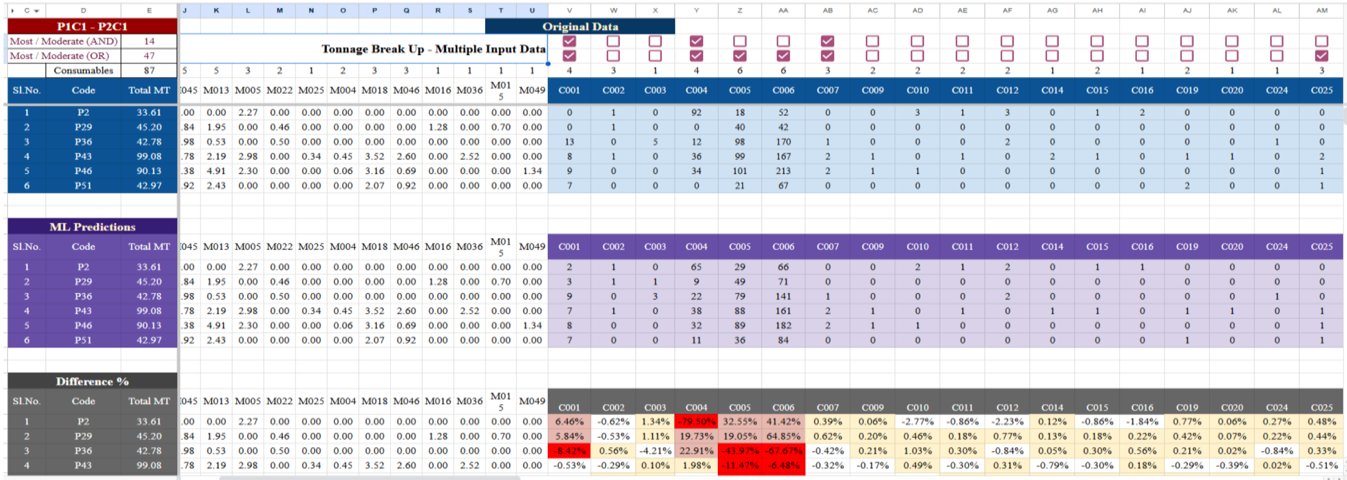
Table 1. Prediction performance by classification group

Group	R^2	MAE (%)	RMSE (%)	MAPE (%)
P1C1 vs P2C1	0.94	4.2	5.1	5.8
P1C2 vs P2C2	0.91	4.5	5.6	6.0
P1C3 vs P2C3	0.92	4.7	5.4	6.2

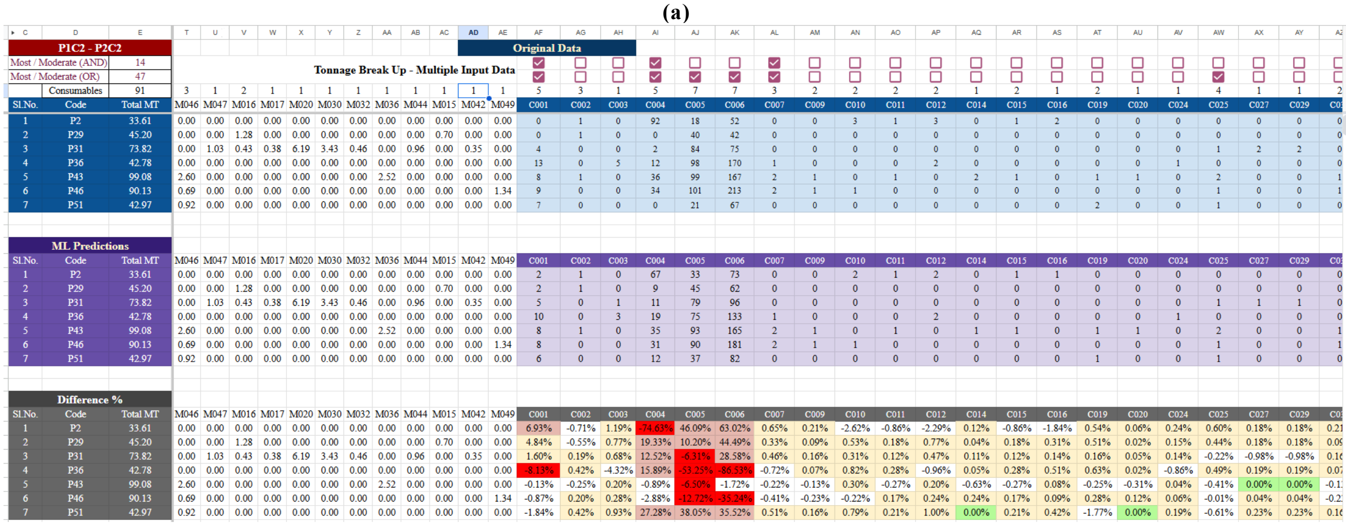
The results in Table 1 show that predictive accuracy remained consistently high across all configurations, with R^2 values above 0.90. Error margins stayed within ±6.2%, meeting industry expectations for procurement-level decision-making.

Figure 3 (a), (b), and (c) shows a comparison of actual test data with machine learning predictions for some consumables in the three project categories. The third table of each figure presents the percentage difference observed between actual values and predicted values.

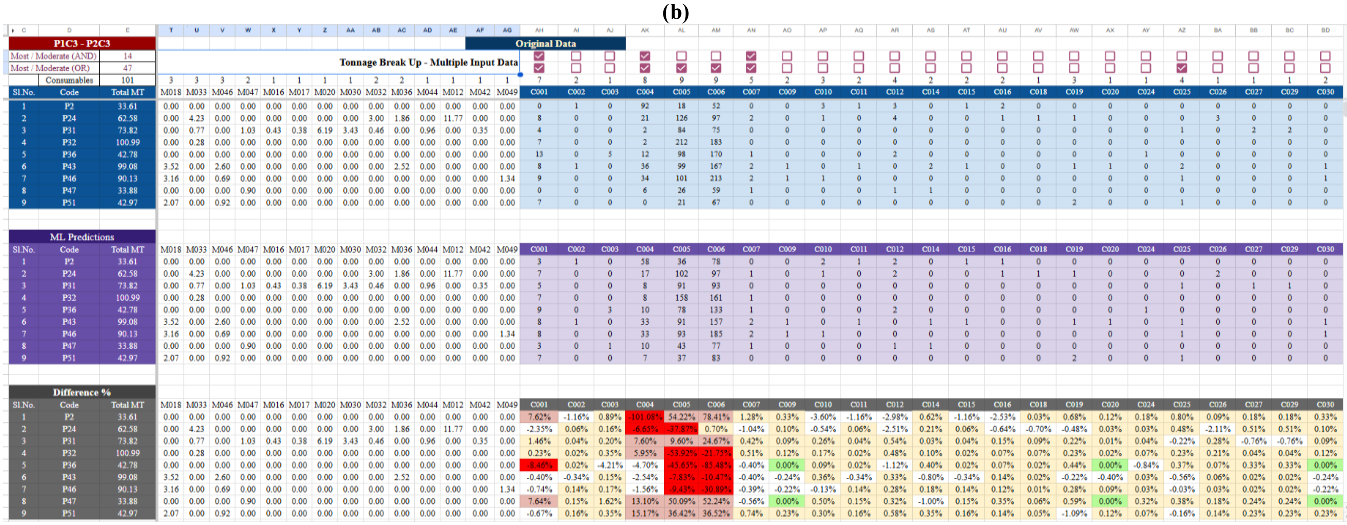
To facilitate interpretation, the forecast value considerably underestimates the actual usage in the highlighted areas. Underprediction here can lead to material shortages or unexpected project delays. Yellow and white highlights stand for predictions within a reasonable tolerance of ±5%, representing high forecast accuracy. Green highlights signify exact matches between actual and forecast values, highlighting the model's skill in accurate estimation. Out of over 100 consumable products, 47 were found to be the most utilized from the data collected through the project. These consumables, as indicated in Figure 3 (a), (b), and (c), as Most / Moderately Used, were ranked highest in the evaluation and validation process to validate the model for real-world use. Notably, consumables with little usage—termed negligible consumables—showed very high predictive consistency. Precisely, 93%, 95%, and 92% of such consumables in all three 3 respective paired sets of categories made entirely accurate predictions. Since they have little effect on total material consumption and expenditure, these products were deemed non-essential to validation and were thus not included in the general performance evaluation.



(a)



(b)



(c)

Fig. 3 Comparison of actual and ML predicted consumables usage under (a) P1C1 vs P2C1, (b) P1C2 vs P2C2, and (c) P1C3 vs P2C3.

5. Results and Discussion

The accuracy of machine learning-based quantity predictions for test samples was checked with statistical methods and is graphically plotted in Figure 4 (a), (b), and (c).

With ±5% tolerance, the highs and lows of percentage deviations for every consumable are marked in the event of estimated surplus or shortage. Additionally, based on each consumable's cumulative percentage from the experimental projects, the model predictions are categorized into high-margin, low-margin, and actual-profit outcomes, as shown in Figures 4 (a), (b), and (c).

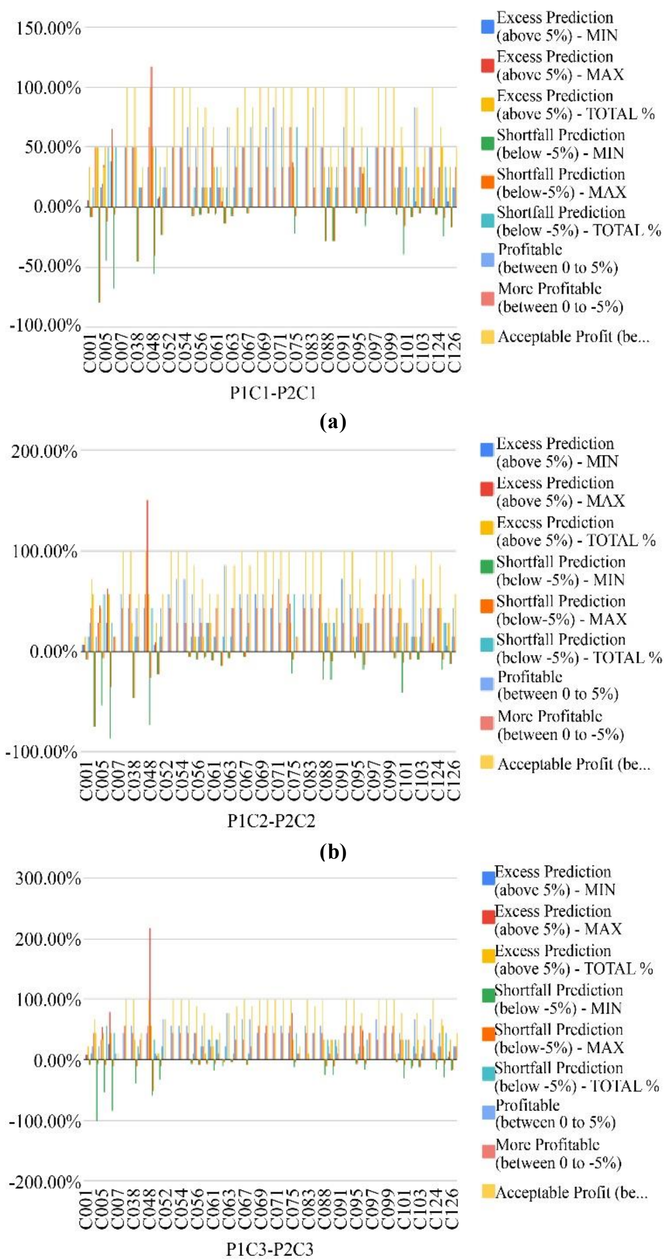


Fig. 4 Statistical analysis of quantitative ML on (a) P1C1 vs P2C1, (b) P1C2 vs P2C2, and (c) P1C3 vs P2C3.

A scenario whereby the machine learning algorithm overestimates the predicted demand for a material is beneficial to the producer. In these cases, predicted demand exceeds reality, thus ensuring the consistent availability of the Materials over the period of the project timeline. This assists in eliminating the risk of shortage within the project and making it possible to reuse excess stock for future purposes, thus avoiding potential delays and expenses. Conversely, forecasted volumes are a major operational issue. A shortfall during project completion requires emergency procurement, generally at higher prices and with minimal vendor flexibility. Besides adding cost, this can also undermine project budget adherence. Mention should be made here that consumables represent a major percentage of production costs in PEB manufacture, often coming close to raw material costs, and thus, correct forecasting is of paramount importance. Where forecasted values match exactly with tendered quantities, the project is considered maximally profitable, realizing desired outcomes with neither excess nor deficiency. Figure 5 consolidates these trends from a bar graph, condensing the distribution of forecast quantities into three buckets: underestimation (shortfall), overestimation (excess), and values within the acceptable tolerance. In all three classification comparisons, the rate of overestimated consumables is around 25%, and the rate of underpredicted items is below 20%. Around 60% of the forecasts fall within the acceptable ±5% tolerance, reflecting effective and balanced forecasting practices. Apart from this, the predictive efficiency of the model is also illustrated in Figure 6, which indicates that all three categories of classification have over 80% of predictions allocated, resulting in fruitful outcomes. It indicates the ability of the model to generate financially rewarding predictions with high reliability.

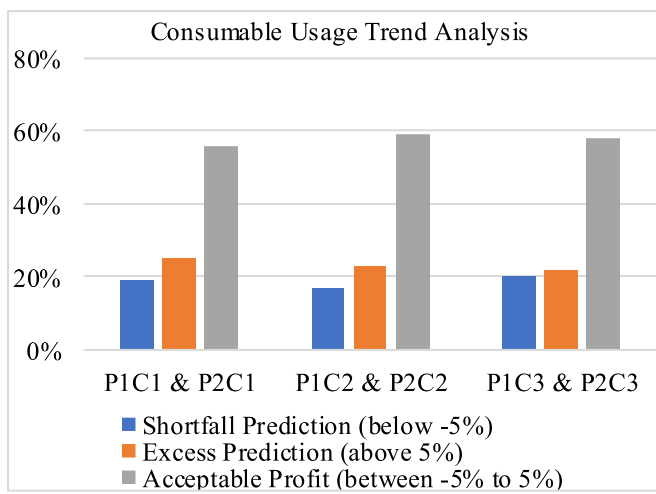


Fig. 5 Shortfall, excess and profitable ML predictions of consumables usage

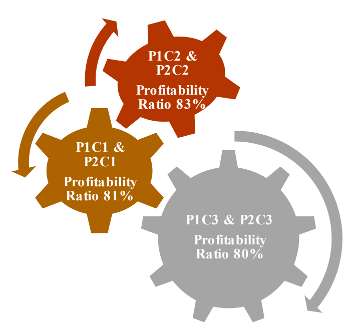


Fig. 6 Overall profit

Inaccurate prediction of consumables can have serious implications for the efficiency and profitability of PEB manufacturing projects. Underestimation often results in the need for emergency procurement during ongoing fabrication activities, which may lead to inflated costs, delays in production, and disruption of sequential operations. Furthermore, rushed procurement typically limits the ability to negotiate optimal pricing, further increasing financial strain. While less disruptive, Overestimation contributes to excess inventory, inefficient capital allocation, and potential material wastage, especially for consumables with limited shelf life. Given that consumable costs in PEB fabrication are comparable to raw material expenses, even small inaccuracies can significantly affect overall project budgets. Therefore, improving prediction accuracy is not merely a technical enhancement—it directly supports better resource planning, cost control, and sustainable manufacturing practices.

6. Conclusion

This research proposes a methodologically sound framework for material need forecasting in Pre-Engineered Buildings (PEBs) fabrication via Random Forest Regression (RFR) and probabilistic classification of comparable projects. With the utilization of total project tonnage as an input and breaking it down into heterogeneous component-specific quantities, the model enables multi-output predictions regarding major fabrication components.

The data was made homogeneous and relevant by splitting 71 recently completed. Projects into P1 and P2 types based on significant structural components and then into combinations C1, C2, and C3 based on their complexity. Hyperparameter tuning via GridSearchCV improved model performance with profitability predictions of 81% for P1C1, 83% for P1C2, and 80% for P1C3 project types. These findings indicate better forecasting accuracy, improved resource planning, and decreased procurement risks, thus forming a scalable and intelligent system for efficient and sustainable planning in PEB construction.

This proposed model approach, compared to existing approaches, can be attributed to several key factors. First, the study uses real-time, factory-level datasets with detailed member-wise tonnage breakdowns, rather than relying on aggregate or assumed values, which are common in prior works. Second, the introduction of probabilistic project grouping (P1C1, P1C2, P1C3) based on fabrication relevance ensures that the model captures structural complexity and fabrication scale more effectively than generalized models. Third, the use of a multi-output Random Forest Regression model enables simultaneous prediction of over 100 consumables, allowing the model to account for interdependencies between materials, which single-output or univariate models cannot capture. These features collectively contribute to the model's superior accuracy, particularly in minimizing prediction errors for high-frequency consumables. In contrast, many state-of-the-art studies reviewed focus on either cost-level forecasting or energy consumption in broader construction contexts, lacking the granularity and industrial relevance achieved in this work.

6.1. Limitations and Future Directions

While the proposed machine learning framework demonstrates strong predictive accuracy and practical value in forecasting consumables for PEB manufacturing, certain limitations should be acknowledged. The model is trained on historical data from a single manufacturing unit, which may limit its generalizability across varying fabrication standards, geographic regions, or production workflows. The exclusion of site-level fabrication and the focus solely on factory-based data may also restrict the model's applicability in hybrid project environments. Furthermore, the current model operates on static project inputs and does not account for time-based variations or supply chain fluctuations that could impact material usage. Prediction accuracy may also be lower for infrequently used consumables due to limited data availability and an imbalance in usage frequency.

Future research may explore dynamic or real-time forecasting models by incorporating time-series datasets and sensor-based inputs to build upon this work. Expanding the dataset to include multiple manufacturing units and cross-regional data will help improve model robustness and generalization. The exploration of modern ML techniques like deep learning, ensemble stacking, or probabilistic regression methods could further enhance prediction accuracy, particularly for rare consumables.

Additionally, integrating predictive outputs with inventory optimization systems can enable automated procurement planning and just-in-time inventory management. Investigating the environmental and economic benefits of predictive consumables planning may also provide broader insights into sustainable and cost-efficient construction practices.

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The research was conceptualized and designed by Author 1 and Author 2. Author 1 and Author 4 were responsible for drafting the manuscript, conducting the investigation, and performing the data analysis. Author 5 contributed to the development of the machine learning model, while Author 2 and Author 3 provided supervision, oversaw the project's administration, and assisted in reviewing and refining the manuscript. All authors have read and approved the final version of the paper.

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