SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V12I6P108

Volume 12 Issue 6, 83-90, June 2025

Original Article

Material Forecasting in PEB Fabrication Using Machine Learning Techniques

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Received: 06 April 2025 Revised: 09 May 2025 Accepted: 08 June 2025 Published: 28 June 2025

Abstract *- This paper presents a machine learning-based predictive model to enhance material forecasting and resource optimization in Pre-Engineered Building (PEB) production. Random Forest Regression, along with GridSearchCV for hyperparameter optimization and training, is utilized in the proposed model. A dataset of 70+ actual-time project executions with careful filtering based on stringent disaggregation requirements, including fabrication completeness, critical components of PEB, and quantity limitations, is trained. Projects are probabilistically differentiated into P1 (AND) and P2 (OR) types and also differentiated into fabrication combinations (C1, C2, C3) based on structural complexity and member contribution. A subset of 47 highly used and influential consumables is chosen from 100 plus consumables commonly used to enhance model performance. The proposed predictive model identifies a profitability percentage of 80% in all the grouped datasets, thereby asserting its feasibility for real-world use. The proposed methodology facilitates proper material planning, minimizes waste in fabrication, and aids in strategic decision-making for medium-to-large-scale industrial PEB projects, thereby driving sustainability and increasing operational efficiency.*

Keywords *- Artificial Intelligence (AI), AI-based training Systems, Machine Learning (ML), Material Forecasting, Pre-Engineered Buildings (PEB).*

1. Introduction

The Introduction frames the emerging significance of Pre-Engineered Buildings (PEBs) in modern construction practice, primarily because of their cost-effectiveness, speed of construction, and design modularity, which is most suitable for commercial and industrial purposes [1, 2]. However, with increased demand comes the challenge of managing resource-intensive fabrication processes that involve complex assemblies of steel components, often under tight deadlines and varying client specifications. In construction manufacturing, especially steel-intensive sectors like PEBs, unplanned procurement and overordering contribute significantly to environmental burden and financial inefficiency. By enabling accurate forecasting of consumables, the proposed model directly supports waste reduction, efficient use of resources, and lower carbon emissions—key pillars of sustainable construction. This aligns with global trends in sustainable manufacturing, as emphasized in studies by Sun et al. (2020) and Samadian et al. (2024), which advocate digital tools for optimizing steel fabrication and minimizing environmental impact [3, 4].

Traditional material estimation in PEB projects often relies on heuristic calculations, engineer experience, or fixed percentage assumptions based on gross tonnage. These approaches lack precision, especially when dealing with complex projects, member configurations, and fabrication requirements. Errors in estimation frequently result in emergency purchases, material wastage, or supply delays, all of which impact profitability and project timelines.

Among the critical issues impacting the PEB industry are inaccurate material estimation and poor resource utilization, resulting in outcomes like over-ordering, delayed projects, over-expenditure, or wasteful use of consumables [5, 6]. This is aggravated by the design variation from project to project since different clients and applications require customizations that change the nature and quantity of fabrication components used.

Despite the growth in automation and digital tools in construction, there remains a significant gap in accurately forecasting consumables at the factory fabrication level using real-time project data. Most existing approaches depend on generalized assumptions, rule-of-thumb estimates, or limited parametric inputs, which fail to account for the probabilistic and component-specific nature of PEB fabrication.

However, with the growing demand for Pre-Engineered Buildings (PEBs), the fabrication process has become increasingly resource-intensive and highly customized. Each project may involve unique configurations of structural members, making material estimation difficult to standardize. Current practices in consumable forecasting typically rely on experience-based heuristics or generic percentage-based formulas, which often lead to over-procurement, underestimation, and procurement delays.

This creates a critical research gap in the construction industry: the absence of reliable, data-driven models tailored specifically for consumables forecasting in factory-based PEB fabrication. Most machine learning applications in construction focus on project scheduling, labour productivity, or cost estimation, with limited attention given to resource-level prediction for fabrication consumables.

To solve these issues, the study suggests a data-driven solution involving the use of Machine Learning (ML) in the form of the Random Forest Regression (RFR) model in conjunction with probabilistic clustering to enhance predictability and optimize production decisions. Using these methodologies on 70+ datasets of real-time implemented Pre-Engineered Building (PEB) projects, this study aims to disaggregate, filter, and cluster similar projects by their components, fabrication quantities, and complexity levels. The enhanced dataset is the foundation for building a reliable predictive model that predicts future resource needs for similar projects [7-9].

In addition, incorporating GridSearchCV in hyperparameter tuning increases the robustness and resistance to overfitting the model and, hence, its generalizability and applicability to real-world environments. [10, 11] Besides enhancing operational efficiency, the research supports strategic planning, cost minimization, and sustainability targets by reducing waste and emergency procurement [12-13].

This study advances the design of artificial intelligence and machine learning technology in the construction sector by providing a scalable framework that works not only in prefabricated engineered buildings but also for other sectors with high manufacturing processes [3, 14, 15].

2. Literature Review

Pre-Engineered Buildings (PEBs) have gained extensive use in the construction industry due to their prefabricated design, affordability, and ability for rapid implementation. Nevertheless, the variability and complexity of PEB projects continue to thwart accurate material estimation and efficient use of resources. These variations typically lead to excessive material usage, shortage, or procurement delays, affecting project durations and profitability [9, 14]. Developing efficient forecasting mechanisms is imperative to optimize fabricating processes and prevent operational inefficiencies.

New advances have made Machine Learning (ML) a strong tool for enhancing predictive performance for construction tasks. Random Forest Regression has been identified as a strong model capable of handling non-linear relationships and high-dimensional data. Consequently, it can model material consumption rates and production needs [16, 17]. Hyperparameter tuning techniques such as GridSearchCV further enhance model accuracy and generalizability, thus reducing the risks of overfitting and enhancing performance on new data [18].

Several studies have explored using Machine Learning (ML) in construction for productivity prediction, scheduling, and material demand forecasting. Sadatnya et al. (2023) applied ML for construction crew productivity using work reports, and Zermane et al. (2024) focused on forecasting material quantities through time series models. These models, however, are limited by their dependence on aggregated or generalized input parameters [1].

Mateus et al. (2022) used shallow and deep neural networks for global steel production forecasting. Sukolkit et al. (2024) developed open inventory forecasting models for the steel industry using business-level data [14, 18]. Unlike these studies, this work focuses on project-specific material usage based on actual fabrication data and integrates component-level significance.

Probabilistic project classification according to fabrication size and the use of the critical elements has also been investigated to enhance dataset homogeneity. Structurally consistent classification ensures the prediction models learn from equivalent projects, making them more reliable and providing consistent output [19, 20]. Strategic classification by such probabilistic methods aids data-driven decision-making for project clustering and resource planning.

Although these technologies have promised much, machine learning within the specific Pre-Engineered Buildings (PEB) production industry remains in its early stages. Most existing research draws on generic or artificial construction data, which is not directly applicable to industrial practice [21, 22]. Furthermore, integrating sustainability-focused metrics, such as reduced waste and improved procurement, into machine learning-based prediction models remains in development. However, it is a promising area for future research [4, 14].

Current studies often lack classification methods that differentiate PEB projects based on structural complexity or member groupings. The use of P1/P2 types and C1/C2/C3 combinations, based on the presence of critical members like columns, rafters, joists, and crane beams, provides a structured foundation for more precise model training.

Furthermore, this model uses multi-output forecasting based on a single numerical input (tonnage), which is rarely implemented in existing research. Classifying consumables into significantly used, moderately used, and rarely used categories is also a unique contribution, enabling better feature selection and interpretability.

In brief, the literature strongly indicates the application of ML methods, particularly Random Forest-based models, towards enhancing material estimation and work efficiency in construction. However, this study uniquely contributes value by implementing such methods on real PEB datasets, incorporating probabilistic clustering and sustainability measures, and filling existing real-world application voids. [14, 22, 23].

3. Methodology

This research aims to develop Machine Learning (ML) algorithms to predict the usage of consumables in the fabrication process of Pre-Engineering Building (PEB) components. The ML is expected to predict optimized consumables usage by training the ML model with available past completed real-time datasets.

Traditional methods, such as quantity-based percentage estimations or rule-of-thumb calculations, fail to capture the variability in consumables required for different fabrication member configurations. This approach surpasses these by leveraging machine learning to capture non-linear relationships and member-specific dependencies in the dataset, offering more refined and contextual predictions that scale with complexity.

Around 70+ real-time project datasets were collected from a Pre-Engineered Building (PEB) Company with its own PEB Manufacturing Unit. The project datasets would consist of 45+ fabrication members fabricated within the factory premises using 100+ consumables in various PEB projects. The methodology flowchart involving the preprocessing of the raw datasets is summarized in Figure 1.

The data cleaning process, after data collection is shown in Figure 1. Stagewise Probabilistic Grouping of Datasets includes the removal of project datasets with quantities not mentioned and ongoing projects since it may impact the accuracy of the analysis to some extent. These exclusions of projects are mainly due to site fabrication or human error since this research focuses only on factory fabrication. The collected data is initially grouped based on the total quantity of each project measured in Metric Tonnes (MT). The next stage of preprocessing involves grouping datasets into quantity ranges. Here, projects with tonnage above 30 MT that go up to 110 MT are considered. Based on the fabrication member study, a few members, such as the column and rafter, are considered the most significant components of PEB, without which the PEB project might be considered incomplete. Type P1 consists of columns and rafter, and type P2 consists of either columns or rafter. Beyond these significant PEB members, a few other similar components impact the overall project.

Accordingly, it is classified into C1, focussing on the combinations of only column and rafter, which focuses on the combinations of C1 members along with eave column and rafter, joist and portal beam, portal column, canopy rafter, and C3, focussing on the combinations of crane beam and jack beam adding upto C1 and C2 members.

The calculated percentage of the number of said members in each combination C1, C2 and C3 under each type P1 and P2 project datasets are categorized. Also, range limits based on the significance of these combination components are set as > 75% of C1 members, > 80% of C2 members % and > 85% of C3 members under each type P1 and P2 grouping, respectively. It is well observed that P1C1 vs P2C1 contains the same number of scrutinized project datasets after completing all the above pre-processing processes, as sorted out in Figure 1. Comparably, P1C2 vs P2C2 and P1C3 vs P2C3 comprise the same project datasets. Hence, further analysis using machine learning algorithms performed on 3 sets of type vs combinations would be enough.

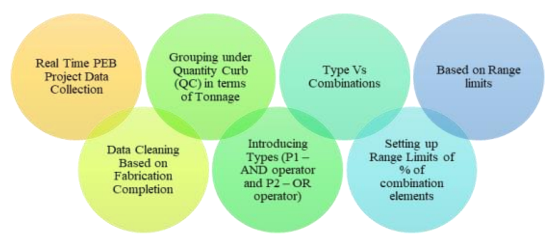


Fig. 1 Stagewise probabilistic grouping of datasets

Table 1. Consumables similarities and maximum usage assessment

Group of projects (Nos)	No. of consumables repeated in a group of projects			Remarks
	P1C1	P1C2	P1C3	
9			15	Most Significantly Used
8			11	
7		15	4	
6	18	11	1	
5	10	5	14	
4	7	10	6	Moderately Used
3	13	10	7	
2	17	16	16 + **3**	Less Significantly Used
1	22	20 + **4**	13 + **11**	
Total	87	87 + **4**	87 + **14**	

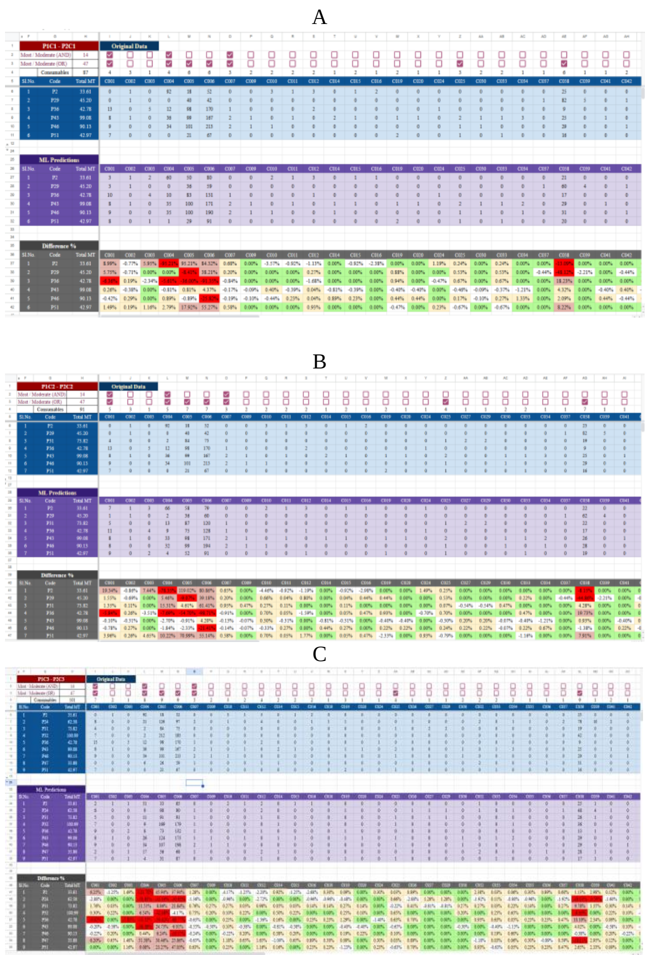


Fig. 2 ML Predictive Modal Performance on (a) P1C1 vs P2C1 (b) P1C2 vs P2C2 (c) P1C3 vs P2C3

Table 1 describes the quantum of consumables used in the maximum number of Pre-Engineering Building (PEB) projects in all 3 categories (P1C1, P1C2 and P1C3). For example, from Table 1 above, 15 different consumables are used in all 9 projects from the P1C3 category. Setting up a baseline, that is, consumables used in 5 or more than 5 numbers projects from all three categories, are then classified as significantly used consumables. Wherein consumables used in (> =) to 3 and <= 5 numbers of projects are named as moderately used consumables.

Similarly, consumables used in (< 3) numbers of projects are named as rarely used consumables, as mentioned in the table above. The boldly highlighted quantity of consumables, 4 from P1C2 and 14 from P1C3, are identified as uncommon consumables used only in P1C2 or P1C3. Interestingly, these unused consumables are within the less significant or rarely used range. Hence, it does not show any major impact on the projects. The above Table 1 also indicates about 55.17%, 56.04%, and 57.43% of the most significant and moderately used consumables in P1C1, P1C2, and P1C3, respectively.

4. Machine Learning for Predictive Modelling and Model Performance

Machine learning models, particularly Random Forest Regression, excel in handling high-dimensional data and mitigating overfitting. Random Forest's ensemble approach has been proven effective in various industrial applications, including PEB fabrication. Further, refine model accuracy by optimizing hyperparameters. These methods collectively address the limitations of traditional forecasting, ensuring adaptability and robustness. The Random Forest Regression model demonstrated high predictive accuracy across all project categories. The model minimized overfitting through hyperparameter tuning and used cross-validation.

To ensure generalizability and avoid overfitting, a 5-fold cross-validation strategy was employed. The dataset was randomly split into five subsets, where four folds were used for training and one for testing in each iteration. This process was repeated five times, with performance metrics averaged over all folds. This approach helps validate the model's consistency across unseen data samples and reflects a more reliable performance measure than a single train-test split.

In Figure 2 (a), (b), (c), the original test data is exclusively compared with ML predictions for each consumable. The ML modal was trained with only the total tonnage of each project as a single input data and its corresponding group of consumables as multiple outputs. The predicted values of all 3 sets of classifications, P1C1 vs P2C1, P1C2 vs P2C2 and P1C3 vs P2C3 subjected to ML modelling, are displayed in Figure 2 (a), (b), (c). The Difference % between the original and ML predictions is tabulated in the 3rd table in Figure 2 (a), (b), (c). In this Difference % table, the red highlights denote the much lower prediction of specified consumables, which would gradually incur heavy losses and a last-minute shortage of fabrication materials. The yellow and white highlights from the same table in Figure 2 (a), (b), (c) highlight the predictions with allowable limits of (+) or (–) 5 %. The green highlights give the same test results, adding to the advantage of using the ML prediction model for better optimizations and accuracy. Among the 100+ consumables, 47 are identified to be used in the maximum number of projects. Hence, these 47 consumables, mentioned as the Most / moderately used consumables in Figure 2 (a), (b), (c), are further concentrated for result interpretations and the validation process. Interestingly, 94%, 93% and 91% of those negligible consumables from P1C1 vs P2C1, P1C2 vs P2C2 and P1C3 vs P2C3, respectively, give 100% positive results. Hence, this negligence may not impact the validation stage.

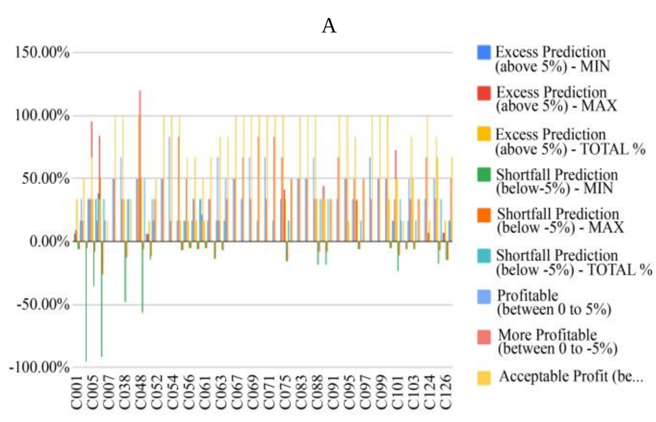
The Introduction frames the emerging significance of Pre-Engineered Buildings (PEBs) in modern construction practice, primarily because of their cost-effectiveness, speed of construction, and design modularity, which is most suitable for commercial and industrial purposes. [1, 2]. However, with increased demand comes the challenge of managing resource-intensive fabrication processes that involve complex assemblies of steel components, often under tight deadlines and varying client specifications

5. Results and Discussion

The results of the test samples for quantitative prediction using machine learning are well analyzed statistically, and the observations are graphically represented in Figure 3 (a), (b), (c).

The application of Random Forest Regression showed significantly improved accuracy in predicting material usage compared to conventional percentage-based forecasts. Manual estimations often have variability ranges above ±10%, especially for rarely used or project-specific consumables. The model kept most predictions within a ±5% tolerance, drastically reducing the risk of under-supply or wastage.

Cross-validation results confirmed the model's robustness. For each classification group (e.g., P1C1 vs P2C1), the average R^2 score ranged from 0.91 to 0.95, and the mean absolute error (MAE) remained below 4.7% of the average consumable usage. These consistent metrics across folds demonstrate that the model performs well across different project samples and does not overfit any specific subset. Considering a ±5% of negligence, the maximum and minimum percentage of the quantity of each consumable predicted to be excessive and in short supply are graphically illustrated in Figure 3 (a), (b), (c). Based on the collective percentage of each consumable in the test sample projects, more profitable, less and the attained profit projects after machine learning prediction, are included in Figure 3 (a), (b), (c). When the ML predicts an excessive quantity over the actual quantity, it becomes more profitable to the industry, saving much money. Since the optimum prediction depending on the trained projects is higher than the original, there are zero chances for additional requirements in the middle of a running project. Hence, no loss shall be incurred. The excess consumables shall be utilized for the next upcoming project.



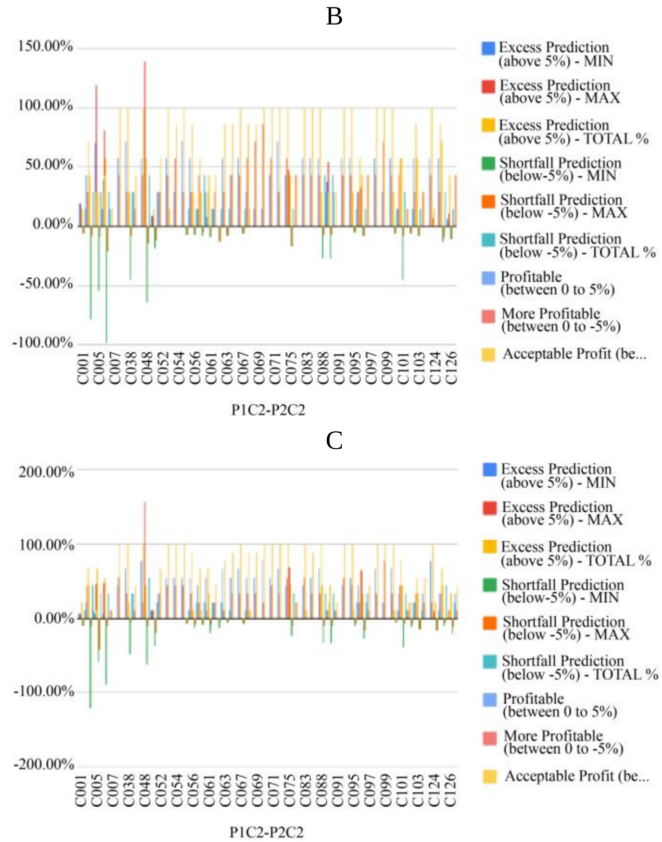


Fig. 3 ML Predictive Modal Performance on (a) P1C1 vs P2C1 (b) P1C2 vs P2C2 (c) P1C3 vs P2C3

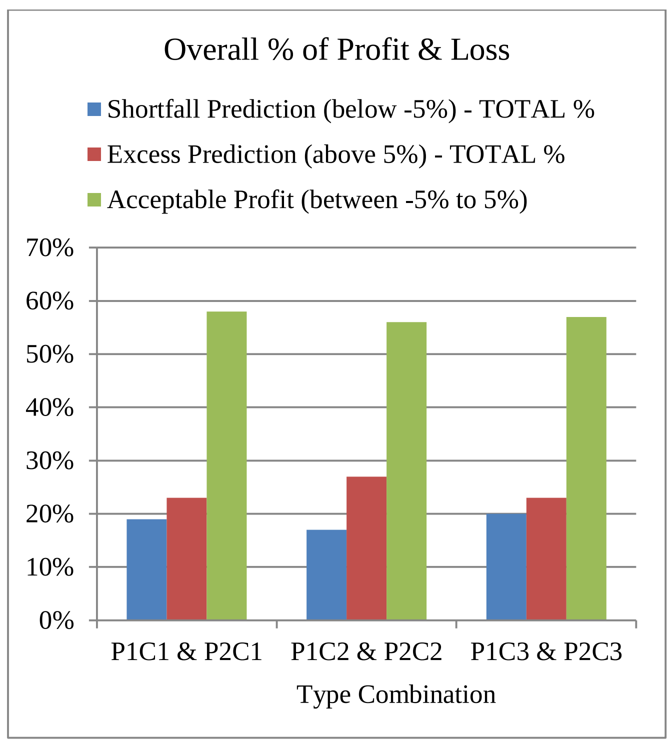


Fig. 4 Shortfall, Excess and Profitable ML predictions of consumables usage

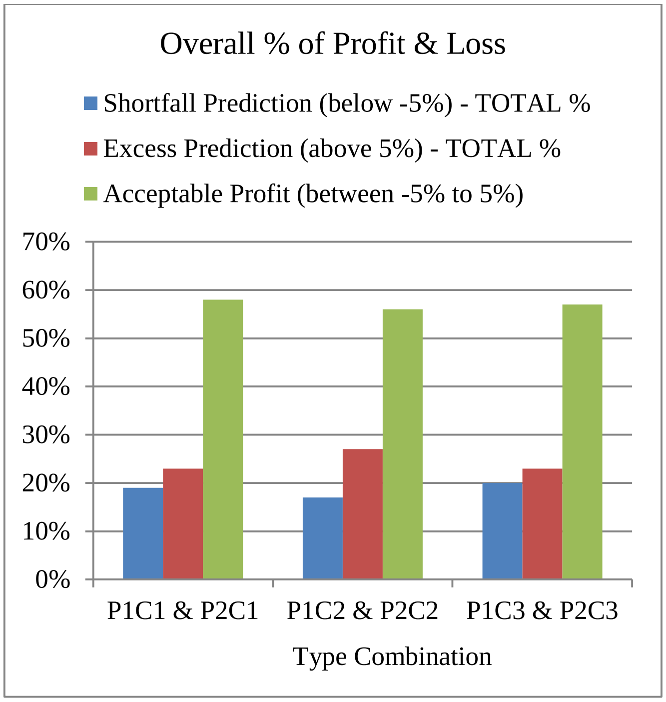


Fig. 5 Overall profit

Meanwhile, when the ML predicts a shortfall of actual quantity, it incurs a huge loss to the industry. Since it would lead unnecessarily to buying additional required Quantities on an ongoing project lead to increased spending with significantly fewer chances of profitable offers by the seller. Also, it affects the initial tendered cost in the projects. These consumables price is one of the most significant costs equivalents to the raw material cost in a PEB industry is to be noted.

When the predicted ML outcome and the actual tendered quantity perfectly match, it becomes a win-win project with actual profit.

The bar chart in Figure 4 gives the cumulative percentages of consumables shortfall, excess and allowable quantity as assessed from ML modal performance. Figure 4 depicts that the Excess prediction falls within more or less 25% in all 3 sets, P1C1 vs P2C1, P1C2 vs P2C2 and P1C3 vs P2C3. The shortfall of consumables, which incurs losses, is only below 20% in all three 3 sets. Approximately 60% of the said profit is attained in all 3 sets.

From the pie chart in Figure 5, it is found that all 3 sets, P1C1 vs P2C1, P1C2 vs P2C2 and P1C3 vs P2C3, show that above 80% of profitable predictions are achieved by the ML prediction model.

In comparison to recent literature, this model demonstrates improved performance. For instance, Zermane et al. (2024) used time-series and ML models for material quantity forecasting but reported MAPE values ranging from 8–12% for real-world applications. Similarly, Mateus et al. (2022) employed shallow and deep neural networks for steel production prediction with error margins exceeding ±10% [14]. In contrast, this approach achieved a MAPE below 6.2% across all classified project types, with R^2 scores exceeding 0.90.

This performance improvement can be attributed to several factors:

i. Use of real, factory-level datasets representing 71 completed PEB projects rather than simulation or design-stage data,
ii. Granular probabilistic classification (P1C1–P2C3) that reduced data heterogeneity and improved model learning,
iii. Focused feature selection by including only the most impactful 47 consumables,
iv. Robust hyperparameter tuning via GridSearchCV, avoiding overfitting and improving generalization,
v. Multi-output regression modelling better captures interdependencies between consumables.

Compared to earlier approaches in the literature, this study demonstrates superior predictive accuracy and field validation, largely due to its integration of domain-specific grouping, real operational data, and a well-tuned ensemble learning model. The ability to generalize across project scales while maintaining low error rates positions this model as a practical advancement over existing methods.

6. Conclusion

This study introduces a technically sound methodology for the optimization of Machine Learning-based Pre-Engineered Building (PEB) fabrication, viz., Random Forest Regression with probabilistic grouping. Methodically disaggregating 71 real-time project datasets, filtering by component relevance, the scale of fabrication, and tonnage of materials, the study introduces high-quality input data for predictive modelling. Classification into project types (P1 and P2) and combinations (C1, C2, C3) enables accurate targeting of medium- to large-scale homogeneous projects. Through thorough consumable analysis, 47 commonly used fabrication resources were determined to be good predictors.

Hyperparameter optimization through Grid Search CV improved model performance, improved prediction accuracy and reduced overfitting. The model showed a profitability rate of 80% for various project classifications, establishing the practical utility of the model. The methodology enables precise material forecasting and resource planning, strategic decision-making, cost optimization, and waste reduction—hence, scalable and sustainable digital transformation in PEB manufacturing. Furthermore, the proposed methodology is not limited to PEBs. It offers a replicable template for other sectors where factory-based production involves a mix of standard and customized components. By adapting the input features and re-training on sector-specific data, industries such as precast concrete systems, containerized modular construction, or aircraft part assembly could benefit from similar predictive frameworks.

6.1. Direction for Future Research

Future work may include integrating real-time fabrication progress data through IoT or RFID technologies, allowing dynamic adjustment of predictions based on actual consumption rates. Additional project attributes, such as the number of bays, machine utilization, and member grouping ratios, could be included to improve input dimensionality. Another promising direction is using deep learning models such as LSTM or XGBoost for sequential and time-sensitive predictions, especially in dynamic factory workflows.

For future studies, incorporating multiple input features beyond tonnage, applying hybrid modelling techniques (e.g., ML + rule-based systems), and expanding the scope to include site-fabricated or modular construction projects can further generalize the model. In addition, evaluating the integration of this forecasting model within Enterprise Resource Planning (ERP) systems or BIM platforms would support broader digital transformation in the construction industry.

Acknowledgements

Authors 1, 2, and 4 conceptualized and designed the research. Authors 1 and 4 wrote the manuscript, investigated, and analyzed the data. Authors 2, 3, and 4 supervised and administered the research and reviewed and edited the manuscript. All authors read and approved the manuscript.

Most significantly, the author wants to convey his gratefulness to God Almighty for leading him through these hardships. Thanks to the Lord Jesus Christ, he could complete this research.

References

[1] Basem S. Abdulfattah et al., “Predicting Implications of Design Changes in BIM-Based Construction Projects through Machine Learning,” *Automation in Construction*, vol. 155, pp. 1-23, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Héctor Cañas et al., “A Conceptual Framework for Smart Production Planning and Control in Industry 4.0,” *Computers & Industrial Engineering*, vol. 173, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Jinpeng Cheng et al., “Machine-Learning-Assisted Design of High Strength Steel I-Section Columns,” *Engineering Structures*, vol. 308, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Pedro M Domingos, “A Few Useful Things to Know About Machine Learning,” *Communications of the ACM*, vol. 55, no. 10, pp. 78-87, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[5] Yu Gao, Jiayuan Wang, and Xiaoxiao Xu, “Machine Learning in Construction and Demolition Waste Management: Progress, Challenges, and Future Directions,” *Automation in Construction*, vol. 162, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] P. Haneena Jasmine, and S. Arun, “Machine Learning Applications in Structural Engineering - A Review,” *IOP Conference Series: Materials Science and Engineering: 6th Biennial International Conference on Emerging Trends in Engineering Science and Technology*, Kerala, India, vol. 1114, no. 1, pp. 1-9, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Seong-Hoon Hwang et al., “Estimation of Economic Seismic Loss of Steel Moment-Frame Buildings Using a Machine Learning Algorithm,” *Engineering Structures*, vol. 254, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Bingzi Jin, and Xiaojie Xu, “Machine Learning-Based Scrap Steel Price Forecasting for the Northeast Chinese Market,” *International Journal of Empirical Economics*, vol. 3, no. 4, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] K. Karthick, R. Dharmaprakash, and S. Sathya, “Predictive Modeling of Energy Consumption in the Steel Industry Using CatBoost Regression: A Data-Driven Approach for Sustainable Energy Management,” *International Journal of Robotics and Control Systems*, vol. 4, no. 1, pp. 33-49, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Balduíno César Mateus et al., “Forecasting Steel Production in the World-Assessments Based on Shallow and Deep Neural Networks,” *Applied Sciences*, vol. 13, no. 1, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] M.Z. Naser, “Machine Learning for All! Benchmarking Automated, Explainable, and Coding-Free Platforms on Civil and Environmental Engineering Problems,” *Journal of Infrastructure Intelligence and Resilience*, vol. 2, no. 1, pp. 1-15, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Astrid M. Oddershede et al., “Formulation of a Manufacturing Strategy Using the House of Quality,” *Procedia Manufacturing*, vol. 39, pp. 843-850, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] Suresh Babu Rajasekaran, “Applications of Machine Learning in Manufacturing: Benefits, Issues, and Strategies,” *International Journal of Computing and Artificial Intelligence*, vol. 4, no. 1, pp. 1-11, 2023. [CrossRef] [Publisher Link]

[14] Christina Reuter, and Felix Brambring, “Improving Data Consistency in Production Control,” *Procedia CIRP*, vol. 41, pp. 51-56, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[15] Amir Sadatnya et al., “Machine Learning for Construction Crew Productivity Prediction Using Daily Work Reports,” *Automation in Construction*, vol. 152, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Delbaz Samadian et al., "Meta Databases of Steel Frame Buildings for Surrogate Modelling and Machine Learning-Based Feature Importance Analysis," *Resilient Cities and Structures*, vol. 3, no. 1, pp. 20-43, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mohamed A. Shaheen, Rebecca Presswood, and Sheida Afshan, "Application of Machine Learning to Predict the Mechanical Properties of High Strength Steel at Elevated Temperatures Based on the Chemical Composition," *Structures*, vol. 52, pp. 17-29, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohammadsadegh Shahrokhishahraki et al., "Machine Learning Predictions for Optimal Cement Content in Sustainable Concrete Constructions," *Journal of Building Engineering*, vol. 82, pp. 1-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Nonthaphat Sukolkit, Sirawadee Arunyanart, and Arthit Apichottanakul, "An Open Innovative Inventory Management Based Demand Forecasting Approach for the Steel Industry," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 10, no. 4, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Wenqiang Sun et al., "Material and Energy Flows of the Iron and Steel Industry: Status Quo, Challenges and Perspectives," *Applied Energy*, vol. 268, pp. 1-15, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Qing Xia et al., "A Method towards Smart Manufacturing Capabilities and Performance Measurement," *Procedia Manufacturing*, vol. 39, pp. 851-858, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[22] Yayin Xu et al., "Machine Learning in Construction: From Shallow to Deep Learning," *Developments in the Built Environment*, vol. 6, pp. 1-13, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Hanane Zermane et al., "Forecasting Material Quantity Using Machine Learning and Times Series Techniques," *Journal of Electrical Engineering*, vol. 75, no. 3, pp. 237-248, 2024. [CrossRef] [Google Scholar] [Publisher Link]