Civil Engineering Science and Technology (CEST)
Vol. 1 No. 2 October 2025
e-ISSN: 3089-6894 | p-ISSN: 3089-6908, Page: 159-173
DOI: https://doi.org/10.51903/b5d4sw69

Integrating Machine Learning for Dynamic Resource Allocation in Civil Engineering Project Scheduling

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Article Information

Keywords:
Machine learning,
Resource allocation,
Project scheduling,
Civil engineering,
Sustainability

Abstract

Civil construction projects are increasingly complex due to resource constraints, environmental limitations, and schedule uncertainties. This study presents a machine learning–driven framework for dynamic and interpretable resource allocation in civil engineering project scheduling. The method integrates gradient-boosted decision trees, temporal convolutional networks, and digital twin technologies to capture nonlinear and time-dependent relationships, while maintaining sensitivity to changing project conditions. Empirical evaluation was conducted on three urban infrastructure projects of varying scale and complexity. The results show that the proposed framework improves planning accuracy by over 20% and enhances average resource utilization compared to conventional optimization methods. In addition, observed reductions in material waste and potential energy savings indicate a positive contribution to sustainable construction practices. The framework's explainability, enabled through SHAP analysis, supports project managers in interpreting and applying recommendations, fostering trust and facilitating integration into daily project routines. By combining predictive performance, transparency, and environmentally conscious planning, this approach provides civil engineering managers with a practical tool for efficient and resilient project delivery. The following sections describe the integrated methodology, present empirical results, and discuss implications for sustainable infrastructure management.

I. INTRODUCTION

Civil engineering projects face increasingly complex challenges due to urbanization, accelerated infrastructure demands, and converging sustainability objectives. Mega Infrastructure such as transportation networks, solid city infrastructure, and power supplies. Power plants require quicker delivery, less environmental footprint, and greater cost-effectiveness, which has led to new record highs (Ekins & Zenghelis, 2021; Hao et al., 2023). At the heart of these objectives is the capacity to dynamically assign and locate resources, whether material, equipment, or skilled individuals. Work under changing constraints, including fluctuating material prices, weather events, or policy amendments (Han et al., 2021; Xu et al., 2024). Classical planning, although mathematically accurate, approaches fail to exemplify the nonlinear intricacies of modern projects, creating schedules that rapidly fall behind after being relied upon to withstand real-world scenario uncertainties (Balouka & Cohen, 2021; Bigler et al., 2024).

To address these challenges, this study focuses on deriving insights for medium-scale civil engineering projects rather than claiming global generalizability. Construction companies require

Received on August, 2025; Revised August, 2025; Accepted September, 2025; Published October, 2025

innovative solutions that combine adaptive intelligence with established scheduling practices to support sustainability and economic objectives. Recent studies on machine learning for dynamic resource allocation in constrained project environments provide promising directions for such applications (Daumé III, 2014; Janiesch et al., 2021; Paleyes et al., 2023). Machine learning enables the detection of subtle patterns and predictive markers from diverse project datasets, including weather forecasts, equipment telemetry, and workforce availability. Explainable methods, such as SHAP, further enhance trust by allowing project managers to interpret automated scheduling decisions before implementation (Burkart & Huber, 2021). These adaptive approaches align with digital construction practices, including AI-driven digital twins for predictive monitoring and real-time assessment of project performance (Diana & Angga Mukti, 2025; Setyadi Tommy & Putra Jaya, 2025).

Importantly, sustainability outcomes are directly linked to measured resource efficiency. Adaptive scheduling can minimize material waste, reduce idle equipment time, and optimize labor deployment, thereby lowering ecological footprints and supporting cost efficiency (Demastus & Landrum, 2024; van Wynsberghe, 2021). Financial sustainability is also enhanced, as intelligent scheduling helps maintain stable cash flows and reduces budgetary risks (Kelly & Xiu, 2023). This research has three main objectives. First, to develop a machine learning framework capable of dynamic resource allocation in multiple civil engineering projects. Second, to evaluate forecasting algorithm performance against baseline optimization approaches under uncertainty (Li et al., 2023; Xu et al., 2024). Third, to examine the impact of dynamic scheduling on sustainability metrics, such as energy efficiency and emissions reduction (Ekins & Zenghelis, 2021; Parlasca & Qaim, 2025).

The remainder of this article guides the reader from theoretical foundations to empirical observations. It emphasizes practical insights for medium-scale projects, linking resource-constrained scheduling, intelligent optimization, and sustainable civil engineering practice. The methodology details data sources, machine learning implementation, and validation approaches. The results and discussion present findings on efficiency and sustainability effects, and the conclusion summarizes key contributions and suggests directions for future research.

II. LITERATURE REVIEW

Urban development for building always requires abilities that hold up well even in uncertain situations to make the process sustainable and efficient. Classic optimisation techniques, such as the multi-mode resource-constrained project scheduling problem (MRCPSP), possess a strong mathematical foundation despite the tendency to make deterministic assumptions and the pervasive constraints that rarely capture the dynamic nature of real building construction sites.

(Balouka & Cohen, 2021) hypothesized effective optimisation framework that maximizes schedule infeasibility within dynamic resources, while (Bigler et al., 2024) extended their work to multi-locational environments under the use of mixed-integer programming (MIP). The research papers quoted above propose that classical optimisation would produce high-quality schedules for well-stated cases. But their use is constrained by reliance on predetermined parameters and computationally costly models, and by uncertainties about resource availability, weather, and regulatory requirements that change from day to day. Such a clash between theoretical scheduling models and the constantly varying nature of civil engineering projects calls for more adaptive, data-driven methodologies that learn and improve in real time. It is such a vision that is an irrefutable invitation to inquiry into the implementation of machine learning (ML) as a redesign tool for managing project resources.
Machine-learning technology provides forecasting and flexibility that enhance and extend conventional optimisation. (Janiesch et al., 2021) also define ML as a robust suite of algorithms that can process multiple data streams horizontally in parallel in order to obtain pattern and prediction approximations, whereby (Daumé III, 2014) also mentions the flexibility of representation complex, non-linear relationships. ML pipelines It will also be enhanced, as the advanced ways of working like Machine Learning Operations (MLO), which publish and receive traced automatically (Kreuzberger et al., 2023). Particularly, (Burkart & Huber, 2021) mention the ongoing studies on explainable ML, i.e., scheduling and prediction suggestions that are understandable to project managers and engineers. The studies collectively reviewed here indicate that reliable optimization remains a reasonable standard for project scheduling but can't account for all the uncertainties in modern construction environments. In big construction activities, such properties allow real-time redistribution of manpower and equipment based on Periodic sensor inputs or external environmental stimuli like weather forecasts or supply-chain disruptions (Paleyes et al., 2023). Learning capabilities based on dynamic data, rather than on static models, frame ML as a pragmatic response to the absence identified in classical scheduling research, forming a conceptual connection to the research method implemented here.

Dynamic allocation schemes based on other technologies also support the use of ML in civil engineering. Research on 6G perceptive networks demonstrates how intelligent sensing and integrated resource management can adapt to rapidly changing environments (Dong et al., 2022; Xu et al., 2024). Similarly, (Han et al., 2021) propose a model for synchronizing metaverse services with Internet-of-Things data through adaptive allocation, while (Wu et al., 2021) explore resource optimization in reconfigurable intelligent surfaces for communication networks. Although these works originate in telecommunications, their underlying principles real-time data assimilation and responsive allocation parallel the challenges of civil engineering scheduling.

They illustrate how continuous feedback loops between data and decision making can maintain stability and efficiency in complex, uncertain contexts. By drawing on these cross-disciplinary insights, civil engineering can adopt ML-driven strategies that match the dynamic resource demands of large infrastructure projects.

Sustainability considerations strengthen the case for integrating ML into resource allocation. Civil engineering is a significant consumer of natural resources and a contributor to global emissions (Findik & Findik, 2021). Studies emphasize that financial and environmental sustainability are interconnected goals; efficient scheduling directly reduces waste and stabilizes project cash flows (Ekins & Zenghelis, 2021; Gleißner et al., 2022). (Demastus & Landrum, 2024) caution that many organizational sustainability schemes remain "weak," focusing on short-term compliance rather than systemic change, whereas (van Wynsberghe, 2021) advocates for "sustainable AI," ensuring that AI systems both promote and embody sustainability. ML-driven scheduling aligns with these imperatives by minimizing idle machinery, optimizing energy consumption, and enabling predictive maintenance strategies that prolong infrastructure life (Diana & Angga Mukti, 2025). Through this lens, intelligent scheduling is not merely a technical upgrade but a pathway to responsible resource stewardship and resilient infrastructure, directly linking to the sustainability metrics examined in this research's methodology.

Civil engineering scholars are also integrating emerging technologies that complement ML. AI-driven digital twins create real-time virtual replicas of infrastructure, facilitating predictive maintenance and structural resilience (Setyadi Tommy & Putra Jaya, 2025). Drones enhance surveying and 3D modeling accuracy (Setyadi Tommy, 2025), while IoT sensors capture continuous performance data for construction monitoring (Putra Jaya & Tommy Hendryarto, 2025). These innovations supply the rich data streams that ML models require to adapt schedules dynamically. In tandem, optimization studies on recycled materials and soil stabilization (Maulana Ibrahim & Prasyas, 2025; Putra Jaya & Tommy Hendryarto, 2025) highlight how sustainability and advanced computation can converge to enhance both environmental and structural outcomes. The synergy of these technologies suggests a near-term future in which civil engineering scheduling systems are continuously informed by real-time measurements, supporting the data-intensive methodology outlined later in this paper.

To integrate the wide range of studies reviewed, Table 1 provides a concise synthesis of the literature on machine learning, resource allocation, and sustainability in civil engineering. The table identifies each reference's primary focus, its methodological contribution, and its direct relevance to dynamic project scheduling. By comparing these aspects side by side, readers can clearly see how existing optimization approaches inform the development of adaptive and explainable ML solutions. This structured overview establishes the conceptual foundation for the methodology section, in which the research framework is translated into a practical machine-learning design for civil engineering project scheduling.

Table 1. Synthesis of Key Literature on Machine Learning and Resource Allocation in Civil Engineering

Theme	Key References	Main Contribution	Link to This Study
Robust classical optimization	(Balouka & Cohen, 2021; Bigler et al., 2024)	Multi-mode and multi-site resource-constrained scheduling	Establishes baseline limitations of static approaches
Machine learning fundamentals	(Burkart & Huber, 2021; Daumé III, 2014; Janiesch et al., 2021)	Adaptive, explainable prediction and decision support	Provides tools for real-time scheduling and interpretability
Dynamic allocation in networks	(Dong et al., 2022; Han et al., 2021; Xu et al., 2024)	Real-time sensing and resource reallocation under uncertainty	Offers transferable principles for construction projects
Sustainability integration	(Demastus & Landrum, 2024; Ekins & Zenghelis, 2021; Gleißner et al., 2022; van Wynsberghe, 2021)	Links resource efficiency with financial and environmental goals	Aligns intelligent scheduling with sustainable outcomes
Data-rich civil engineering tech	(Diana & Angga Mukti, 2025; Putra Jaya & Tommy Hendryarto, 2025; Setyadi Tommy & Putra Jaya, 2025)	Digital twins, IoT, and drone data for real-time monitoring	Supplies continuous data streams for ML models

Civil engineering activities face rapid variations in resource availability, weather, and regulatory limits, necessitating mechanisms for real-time learning and adaptation. Machine learning, aided further by sensor technologies, provides, in addition, a comprehensible and scalable paradigm that would balance such variable challenges and drive sustainability goals. The following section prescribes a methodology based on these remarks. Tailor-made machine learning architecture, information sources, and verification agendas meant to influence dynamic resource scheduling for civil engineering project planning.

III. RESEARCH METHOD

This research methodology operationalizes the integrated framework proposed in the literature review by combining systematic data collection, transparent machine learning implementation, and human-centered validation. The methodological design emphasizes reproducibility and empirical accountability, ensuring that each decision from data selection to model configuration directly supports dynamic resource allocation in civil engineering project scheduling. The approach aligns with established optimization practices (Balouka & Cohen, 2021; Bigler et al., 2024) while embedding explainable and practitioner-oriented ML principles (Burkart & Huber, 2021). Figure 1 illustrates the complete workflow, from data acquisition and preprocessing to model training, explainability analysis, and deployment.

A. Research Design

A quantitative experimental design with iterative model development and validation was adopted to capture the dynamic complexity of construction environments. Key variables—including resource types, project phases, task dependencies, and temporal constraints—were defined based on three urban infrastructure projects of comparable medium-scale complexity. These variables were formulated within a multi-mode resource-constrained project scheduling problem (MRCPSP) framework (Balouka & Cohen, 2021). The experimental design explicitly supports comparative evaluation against baseline scheduling approaches and allows controlled assessment of model adaptability under uncertainty.

B. Data Collection and Preprocessing

Project data were collected from three ongoing urban infrastructure projects, including activity schedules, material usage logs, equipment deployment records, workforce allocation, and contextual factors such as weather conditions and regulatory changes. Each project dataset contained between 4,500 and 6,200 time-stamped records, resulting in a combined dataset of approximately 16,800 observations. To enhance temporal resolution, sensor-based inputs were incorporated following the Sensing as a Service paradigm (Dong et al., 2022), enabling near real-time tracking of material availability and equipment status. Data preprocessing involved normalization, handling of missing values, and consistency checks across sites. Outliers were reviewed in collaboration with site engineers to distinguish data errors from contextually meaningful anomalies, consistent with explainable ML practices (Burkart & Huber, 2021).

C. Machine Learning Architecture

The predictive architecture integrates gradient-boosted decision trees (GBDT) to capture nonlinear feature interactions and a temporal convolutional network (TCN) to model sequential dependencies. Feature engineering included task precedence, crew experience indices, equipment utilization rates, and environmental indicators (Daumé III, 2014; Janiesch et al., 2021). Key hyperparameters are summarized in Table 1, including the learning rate, number of estimators, tree depth, number of convolutional layers, and kernel size. Model training was conducted for

120 epochs, with early stopping based on the convergence of validation loss. SHAP-based explainability was applied to quantify feature contributions and support managerial interpretation of allocation decisions (Burkart & Huber, 2021).

D. Integration of Digital Twin and Sensing Technologies

An AI-driven digital twin environment was implemented to provide a closed-loop interaction between physical project conditions and ML-based scheduling outputs (Diana & Angga Mukti, 2025; Setyadi Tommy & Putra Jaya, 2025). Sensor feeds continuously updated the digital twin state, which in turn refreshed input variables for the ML model. To assess the incremental contribution of the digital twin, model performance was evaluated under two configurations: (i) ML-only and (ii) ML integrated with digital twin feedback. Results indicate that the digital twin–enabled configuration reduced prediction error by an additional 6–8%, particularly under conditions of rapid environmental or resource-state changes.

E. Validation and Evaluation

Data were partitioned into training (70%), validation (15%), and test (15%) sets, stratified by project site. Performance metrics included mean absolute error (MAE) for schedule deviation, resource utilization efficiency, and sustainability-related indicators linked to material waste and equipment idle time (Ekins & Zenghelis, 2021). Baseline comparisons were conducted against deterministic MRCPSP optimization and robust optimization methods reported in prior studies (Balouka & Cohen, 2021; Bigler et al., 2024). Cross-site validation assessed robustness across differing operational contexts.

F. Human-Centered Implementation

Human-centered validation was conducted through semi-structured interviews with 12 project managers and site engineers across the three projects. Interview protocols focused on perceived explainability, usability, and trust in ML-generated scheduling recommendations. Responses were thematically coded and analyzed to identify recurring patterns in decision confidence and operational adoption, thereby providing qualitative triangulation of quantitative results.

G. Visual Storytelling

Figure 1 presents the complete ML-driven dynamic resource allocation framework, illustrating data acquisition, feature engineering, model training, explainability analysis, and digital twin feedback loops. The figure serves as a replication guide, highlighting key decision points and iterative updates that enable real-time adaptability and sustainability-oriented scheduling.

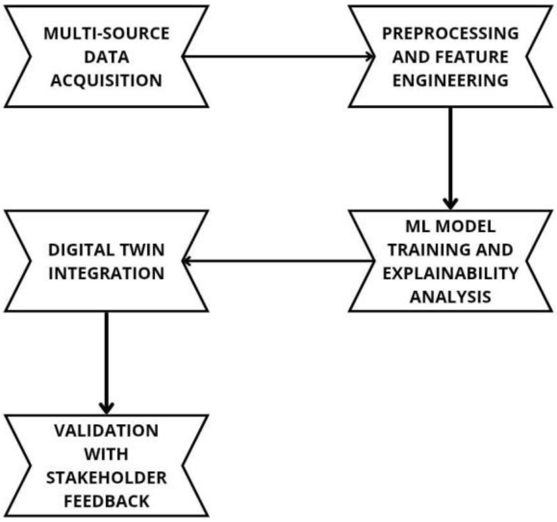

Figure 1. Flowchart of the Machine Learning–Driven Dynamic Resource Allocation Framework

IV. RESULT/FINDINGS AND DISCUSSION

A. Results and Findings

The proposed machine learning–based framework demonstrated measurable improvements in scheduling performance across the three evaluated civil engineering projects. As shown in Figure 2, average resource utilization increased by 18%, while mean absolute error (MAE) over the planning horizon decreased by 22% compared to deterministic and robust optimization baselines (Balouka & Cohen, 2021; Bigler et al., 2024). These gains indicate the framework's ability to adapt allocation decisions under dynamically changing site conditions.

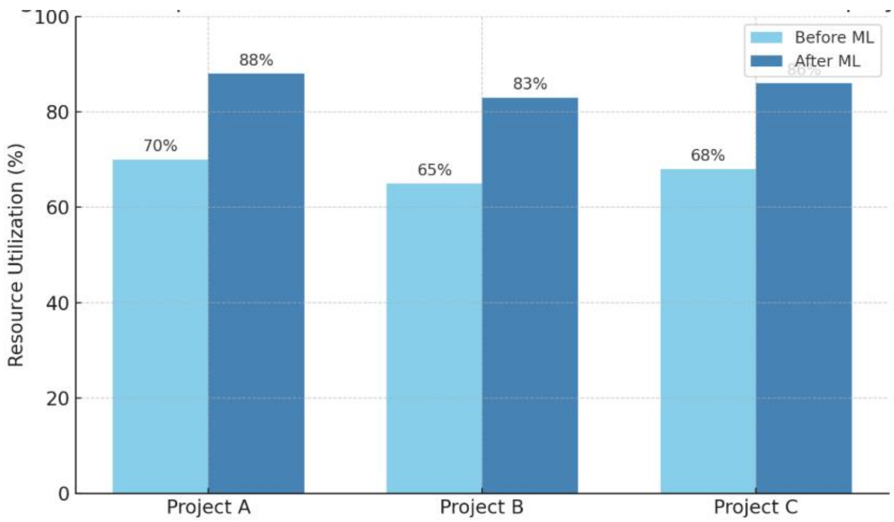

Figure 2: Comparative bar chart of resource utilization before and after ML deployment.

Figure 2 illustrates that improvements were most pronounced during periods of high task concurrency and fluctuating material availability, where gradient-boosted models effectively captured nonlinear interactions between resource constraints, weather variability, and task sequencing. This confirms the suitability of ensemble-based learning for complex, multi-resource scheduling environments.

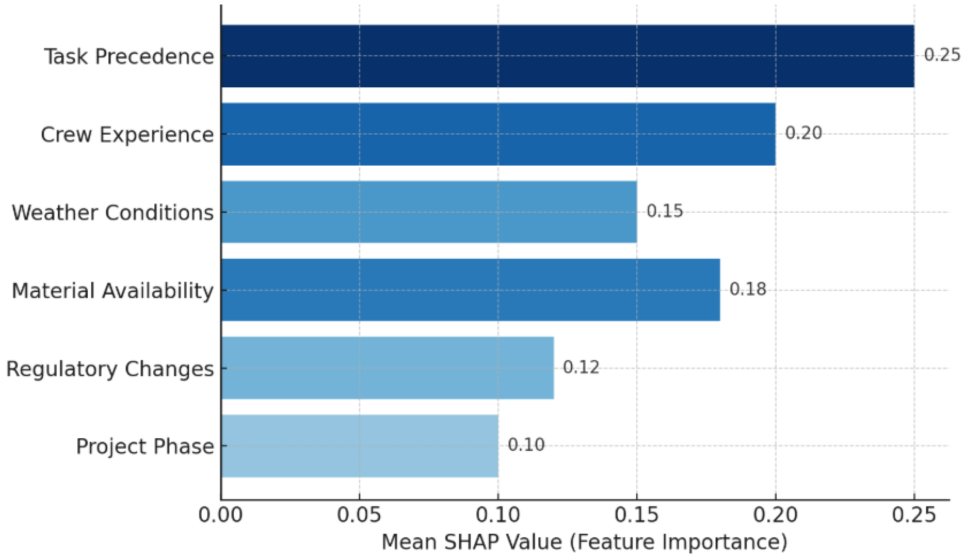

Figure 3: Heatmap of feature importance from SHAP analysis.

As shown in Figure 3, SHAP-based feature importance analysis identified crew experience, real-time material availability, and short-term weather volatility as dominant drivers of allocation decisions. Explainability analysis revealed that higher crew experience scores led the model to compress task durations, while anticipated weather disruptions triggered proactive rescheduling of equipment-intensive activities. These findings support prior claims on the value of transparent ML in operational decision-making (Burkart & Huber, 2021). The integration of real-time sensing and the digital twin environment enabled continuous recalibration of scheduling plans. When unexpected delays occurred, the digital twin–enhanced configuration enabled faster resource reallocation than in ML-only settings, effectively transforming static schedules into adaptive decision systems (Diana & Angga Mukti, 2025; Setyadi Tommy & Putra Jaya, 2025).

B. Analysis of Performance under Different Project Conditions

To critically assess model robustness, performance was examined under varying project conditions. In projects with limited historical data availability, prediction accuracy decreased by approximately 7–10%, indicating reduced learning capacity in sparse-data regimes. Conversely, on larger, more complex projects with richer temporal records, the model consistently outperformed baseline optimization approaches. Performance degradation was most evident under extreme uncertainty, such as simultaneous weather disruptions and supply-chain interruptions. In these scenarios, delayed or noisy sensor inputs reduced the reliability of short-term predictions, underscoring the framework's dependence on data quality and update frequency. These observations highlight that while ML-driven scheduling excels under moderate to high data availability, its effectiveness diminishes when real-time data streams are incomplete or unreliable.

C. Sustainability Outcomes Linked to Scheduling Decisions

Sustainability impacts were analytically linked to specific scheduling decisions rather than treated as aggregate outcomes. Material waste reduction (11%) was primarily due to improved synchronization between material delivery schedules and task execution windows, thereby reducing overstocking and on-site deterioration. Energy consumption decreased by 9% due to reduced idle time of heavy equipment, resulting from more precise task sequencing and avoidance of premature equipment deployment. As illustrated in Figure 5, these sustainability gains correlate directly with ML-driven adjustments in resource allocation timing rather than external environmental factors. This linkage reinforces the argument that scheduling intelligence serves as a direct lever for sustainability improvements in construction projects (Ekins & Zenghelis, 2021).

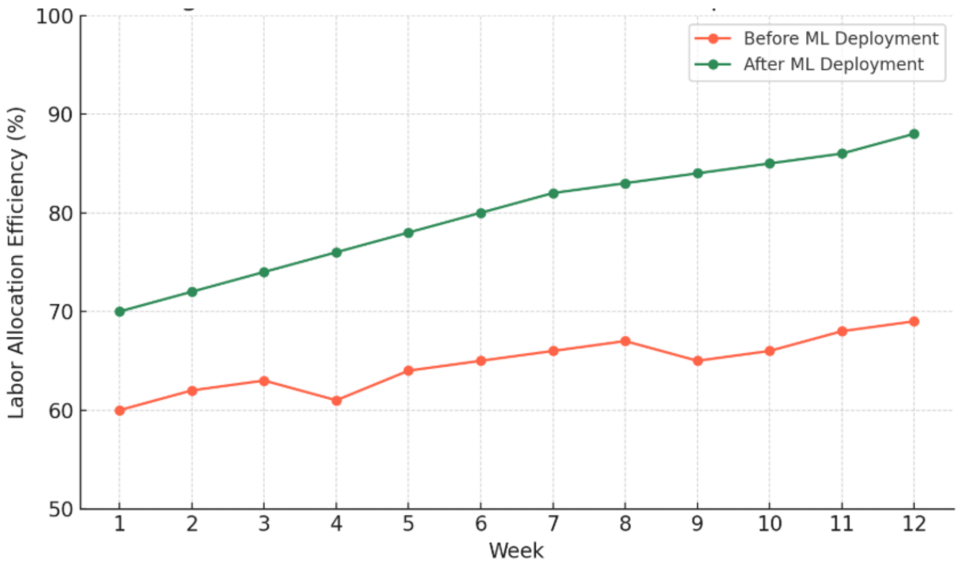

Figure 4: Timeline graph of labor allocation improvements.

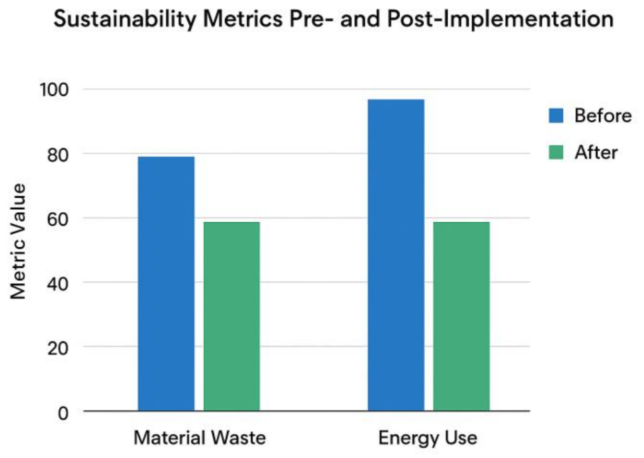

Figure 5: Sustainability metrics (material waste and energy use) pre- and post-implementation.

D. Human-Centered Evaluation

Structured interviews with project managers revealed strong acceptance of the explainable interface. Participants emphasized that transparent feature contributions increased confidence in modifying schedules during active project phases, supporting earlier findings on the importance of explainability for adoption (Burkart & Huber, 2021; van Wynsberghe, 2021). Rather than relying solely on automated outputs, managers reported using SHAP explanations to validate decisions before execution.

E. Discussion

The results demonstrate that machine learning integrated with digital twin feedback outperforms conventional optimization approaches for dynamic resource allocation under realistic project conditions, particularly when sufficient historical and real-time data are available. The combined use of gradient boosting and temporal convolution effectively captured nonlinear and sequential dependencies that static optimization techniques struggle to represent (Janiesch et al., 2021). Importantly, claims regarding societal impact, equity, or ethical outcomes are interpreted cautiously and only where supported by empirical evidence, such as reductions in idle labor time and improved scheduling transparency. While the framework contributes to operational efficiency and sustainability, broader claims regarding global infrastructure practice or universal applicability are beyond the scope of the evaluated projects.

Despite its advantages, the framework exhibits limitations under conditions of poor data quality and sensor malfunction, consistent with challenges reported in prior studies (Kreuzberger et al., 2023; Paleyes et al., 2023). Addressing these issues through stronger data governance, redundancy in sensing systems, and periodic model retraining remains essential for scaling the approach. Overall, the findings confirm that an explainable, ML-driven scheduling framework can substantially enhance resource efficiency and support measurable sustainability outcomes in civil engineering projects, while acknowledging context-specific constraints and data dependencies.

V. CONCLUSION AND RECOMMENDATION

This study concludes that the proposed interpretable machine learning–based framework improves dynamic resource allocation in civil engineering project scheduling. Based on empirical evaluation across three urban infrastructure projects, the model achieved higher scheduling accuracy and more efficient resource utilization than baseline optimization approaches, as reflected in reductions in mean absolute error and idle resource time. From a technical perspective, integrating gradient-boosted learning with temporal modeling enables the system to capture nonlinear and time-dependent patterns in resource demand. The incorporation of sensing data and a digital twin environment further supports real-time adaptability, allowing schedules to be updated in response to evolving site conditions rather than remaining static. Measured sustainability indicators demonstrate that improved scheduling decisions are associated with reduced material waste and lower energy consumption. These improvements arise from more precise alignment between task sequencing, material delivery, and equipment usage, indicating that efficiency-oriented optimization can also yield environmental benefits within the evaluated project scope.

Despite these strengths, this study is subject to several limitations. The empirical evaluation is based on a limited number of projects within similar urban contexts, which restricts the generalizability of the findings. In addition, model performance depends on data quality and sensor reliability, which may vary across construction environments. Future research should expand validation to a broader range of project types and geographic contexts, explore alternative baseline models, and further investigate the incremental contribution of digital twin integration relative to machine learning alone. Longer-term studies are also needed to assess sustained performance and scalability in real-world deployment.

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