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A Comprehensive Review of Machine Learning and Multi-Criteria Decision Analysis in Construction Delay Management

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Abstract

Construction delays remain a critical challenge globally, significantly affecting project performance metrics such as cost, schedule adherence, quality, and safety. Traditional methods like the Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) are widely used but lack the predictive capabilities and adaptability required for dynamic project environments. Machine Learning (ML) and Multi-Criteria Decision Analysis (MCDA) have emerged as innovative tools for addressing these limitations. ML excels in predicting delay impacts by analysing historical data and uncovering hidden patterns, while MCDA provides a structured framework for prioritizing delay factors based on their influence on project performance. This paper provides a comprehensive review of the application of ML and MCDA in construction delay management, highlighting their strengths, limitations, and potential integration. The review identifies research gaps, including the need for hybrid frameworks that combine predictive insights with decision support. It proposes future directions to develop real-time tools for delay mitigation, ultimately enhancing construction project outcomes through data-driven decision-making.

1. Introduction

Construction delays are a pervasive issue globally, causing significant disruptions to project timelines, budgets, and overall performance metrics [1], [2]. These delays often stem from diverse factors, including resource shortages, adverse weather conditions, labor disputes, and regulatory challenges [3]. The ripple effects of delays, such as cost overruns, schedule deviations, and compromised quality, not only affect stakeholders but also undermine the success of construction projects [4]. Traditional approaches like the Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) have been instrumental in project planning and scheduling [5], [6]. However, these methods often fall short in adapting to real-time dynamics and addressing the multifaceted interdependencies of delay factors, limiting their efficacy in proactive delay mitigation [7], [8], [9]. Emerging technologies, particularly Machine Learning (ML) and Multi-Criteria Decision Analysis (MCDA), offer promising solutions to bridge these gaps. ML leverages historical data to predict delay impacts with high accuracy, enabling stakeholders to identify potential risks and develop effective mitigation strategies [10], [11]. Simultaneously, MCDA provides a systematic approach to prioritize delay factors based on their relative impact on performance metrics, facilitating resource optimization and informed decision-making [12], [13]. By integrating ML's predictive capabilities with MCDA's prioritization strengths, a hybrid framework can address the limitations of traditional methods, offering a dynamic, data-driven approach to construction delay management. This paper reviews advancements in ML and MCDA applications, highlights their synergies, and explores the potential for integrated frameworks to enhance project performance.

2. Methodology of the Review

2.1. Scope of the Review

The review aims to evaluate the application of ML and MCDA techniques in identifying, predicting, and mitigating construction delays. The scope includes studies focusing on:

- Predictive analytics in construction delay management using ML techniques.
- Prioritization and decision-support frameworks employing MCDA.
- Hybrid frameworks integrating ML and MCDA.
- Studies published in peer-reviewed journals, conference proceedings, and relevant industry reports.

2.2. Search Strategy

A systematic literature search was conducted to ensure comprehensive coverage of relevant studies. The search strategy employed is summarized in Table 1.

Table 1 Search Strategy and Inclusion Criteria

Criteria	Details
Databases Searched	Scopus, Web of Science, Google Scholar, IEEE Xplore, ScienceDirect
Keywords	"Construction delays," "Machine Learning in construction," "MCDA in construction," "Predictive analytics," "Hybrid frameworks in delay management"
Time Frame	Publications from 2010 to 2024
Inclusion Criteria	Peer-reviewed studies, relevance to ML/MCDA in construction, English language, and full-text availability
Exclusion Criteria	Non-English papers, opinion articles, and studies unrelated to delay management or construction projects

The search process included reviewing abstracts, keywords, and titles to filter relevant studies, followed by full-text assessment for eligibility.

2.3. Data Extraction and Organization

Data extraction was carried out using a standardized form to ensure consistency. Key information extracted from the studies included:

- Publication Details: Title, authors, year, and source.
- Focus Areas: ML techniques, MCDA methods, hybrid approaches, and application context.
- Findings: Key results, strengths, limitations, and gaps identified.
- Metrics: Performance metrics such as accuracy (for ML) and decision outcomes (for MCDA).

The extracted data was organized thematically into categories such as predictive analytics, prioritization frameworks, and hybrid approaches.

2.4. Data Synthesis and Analysis

The extracted data was synthesized to identify common themes, patterns, and gaps in the literature. Quantitative and qualitative findings were analyzed as follows:

- Quantitative Synthesis: Aggregating performance metrics of ML models and decision outcomes of MCDA frameworks.
- Qualitative Synthesis: Identifying strengths, limitations, and contextual applications of the reviewed studies.
- Thematic Analysis: Grouping studies based on methodologies, findings, and research gaps to provide actionable insights.

2.5. Review Validation

The validity of the review was ensured through:

- Peer Review: Seeking feedback from experts in construction management and predictive analytics.
- Consistency Checks: Cross-checking extracted data for accuracy and relevance.
- Coverage Assessment: Ensuring the inclusion of key studies across diverse geographic and project contexts.

This methodology ensured that the review was comprehensive, systematic, and aligned perfectly
With its objectives offer promising solutions to bridge these

3. Overview of Construction Delay Factors

Construction delays significantly impact project

Performance, manifesting in cost overruns, schedule deviations, and compromised quality [14]. These delays can be broadly categorized into external factors, resource-related issues, management challenges, and technological problems. External factors, such as adverse weather conditions and delays in regulatory approvals, disrupt timelines and inflate costs due to extended project durations [15]. Resource-related issues, including material shortages and labor disputes, are among the most frequent causes of delays, leading to productivity losses and scheduling conflicts [7]. Management challenges, such as poor planning, inadequate coordination, and miscommunication among stakeholders, exacerbate inefficiencies and increase dissatisfaction among project participants [16]. Lastly, technological issues, including equipment malfunctions and the lack of advanced tools, further hinder project progress by causing interruptions and resource wastage [17]. The interplay of these factors often creates a cascading effect, where one issue amplifies others, underscoring the complexity of delay management [18]. Identifying and addressing these factors is crucial, as they serve as the foundation for deploying advanced predictive tools like Machine Learning (ML) and prioritization frameworks such as Multi-Criteria Decision Analysis (MCDA) to mitigate their impact effectively. Table Table 2 shows Categories of Construction Delay Factors.

Table 2 **Categories of Construction Delay Factors**

Category	Examples	Impact on Project Performance
External Factors	Weather, regulatory approvals	Increased costs, extended timelines
Resource-Related Issues	Material shortages, labor disputes	Reduced productivity, scheduling conflicts
Management Challenges	Poor planning, miscommunication	Inefficiencies, stakeholder dissatisfaction
Technological Issues	Equipment breakdowns	Delayed activities, resource wastage

4. Machine Learning in Construction Delay Management

4.1. Techniques and Applications

Machine Learning (ML) techniques have become increasingly effective in addressing construction delays by providing predictive insights and identifying key contributing factors. These techniques leverage historical data to model relationships between delay factors and project outcomes, enabling stakeholders to make informed decisions. Table 3 summarizes the key ML techniques, their applications, strengths, and limitations. Random Forest (RF) has been widely applied to predict critical delay factors, demonstrating robustness to noise and high accuracy in predictions [1]. However, its computational demands can be challenging, especially for large datasets. Artificial Neural Networks (ANN) excel in capturing complex, non-linear relationships between variables, making them suitable for delay factor analysis in intricate construction projects [9]. Despite their capability, ANNs require significant amounts of training data, which may not always be available. Support Vector Machines (SVM) are effective for classifying delay causes and are particularly useful for smaller datasets, but their scalability is limited when applied to larger, more complex projects [5]. Lastly, Decision Trees (DT) are praised for their simplicity and interpretability, making them accessible tools for identifying key delay contributors. However, they are prone to overfitting, which can compromise their predictive reliability [16]. These ML techniques provide valuable tools for predicting and mitigating construction delays, but their effectiveness is often contingent upon data quality, model selection, and context-specific applications. Understanding their strengths and limitations allows project managers to select the most appropriate techniques for their specific needs.

4.2. Strengths and Limitations

Machine Learning (ML) techniques offer significant strengths in addressing construction delays, primarily due to their ability to provide high predictive accuracy and identify hidden patterns within complex datasets. These capabilities allow ML models to analyze multiple variables simultaneously, uncover correlations that may not be immediately apparent, and forecast the potential impacts of delay factors on project outcomes [8], [11]. Furthermore, ML techniques such as Random Forest and Artificial Neural Networks have shown robustness in handling noisy data and modeling non-linear relationships, making them highly suitable for the multifaceted nature of construction projects [13]. However, the application of ML in construction delay management is not without its limitations. Most ML models require extensive preprocessing of data, including handling missing values, normalizing variables, and encoding categorical data, which can be time-consuming and resource-intensive. Additionally, some advanced ML models, such as Neural Networks, often face challenges related to interpretability, making it difficult for stakeholders to understand how predictions are generated and to gain actionable insights. These limitations highlight the need for careful model selection, sufficient data availability, and a balance between complexity and usability to maximize the utility of ML in managing construction delays effectively. Table 3 shows Machine Learning Techniques in Construction Delay Management.

Table 3 Machine Learning Techniques in Construction Delay Management

Machine Learning Technique	Applications	Strengths	Limitations
Random Forest (RF)	Predicting critical delay factors [19]	Robust to noise, high accuracy	High computational cost
Artificial Neural Networks (ANN)	Modeling complex relationships between variables [20]	Handles non-linear data well	Requires extensive training data
Support Vector Machines (SVM)	Classifying delay causes [21]	Effective for small datasets	Limited scalability for large datasets
Decision Trees (DT)	Identifying key delay contributors [12]	Simple and interpretable	Prone to over fitting

5. Multi-Criteria Decision Analysis In Construction

5.1. MCDA Techniques

Multi-Criteria Decision Analysis (MCDA) techniques are widely used in construction management to evaluate, rank, and prioritize factors influencing project performance. These techniques provide structured frameworks for addressing complex, multi-dimensional problems by considering both qualitative and quantitative criteria. Table 4 summarizes the key MCDA techniques, their applications, strengths, and limitations. The Analytic Hierarchy Process (AHP) is a popular MCDA method for weighting and ranking factors based on pairwise comparisons. Its simplicity and ease of implementation make it a preferred choice for prioritizing delay factors; however, the method can become time-consuming for projects with a large number of criteria or alternatives [9]. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) excels in ranking alternatives by evaluating their proximity to an ideal solution, allowing decision-makers to consider both qualitative and quantitative criteria simultaneously. Nevertheless, TOPSIS relies heavily on the accuracy of assigned criteria weights, which can affect the reliability of its results [5], [7]. Lastly, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method captures the interdependencies among delay factors, offering a dynamic perspective on their relationships. While effective for smaller datasets, DEMATEL may become overly complex when applied to large-scale projects [15].

5.2. Applications and Benefits

MCDA techniques, such as AHP and TOPSIS, have been widely applied in construction to prioritize delay factors, allocate resources, and select contractors. For example, AHP has proven effective in contractor selection, enabling decision-makers to rank alternatives based on multiple dimensions, such as cost, experience, and quality [21]. Similarly, TOPSIS has been used to evaluate project risks and rank mitigation strategies, supporting informed decision-making under uncertainty. These techniques provide a structured and transparent approach to managing complex decision problems, ensuring that stakeholders can focus on the most critical factors affecting project performance. By integrating these tools with predictive analytics, such as Machine Learning, decision-makers can further enhance their ability to anticipate and address construction delays effectively. Table 4 MCDA Techniques in Construction Management.

Table 4 MCDA Techniques in Construction Management

MCDA Technique	Applications	Strengths	Limitations
AHP	Weighting and ranking delay factors [6]	Easy to understand and implement	Time-consuming pairwise comparisons
TOPSIS	Ranking alternatives based on criteria [15]	Handles both qualitative and quantitative data	Requires accurate criteria weights
DEMATEL	Identifying interdependencies among delay factors [11]	Captures relationships effectively	May become complex for large datasets

6. Hybrid ML-MCDA Frameworks

6.1. Integration Approaches

Integrating ML and MCDA involves leveraging their respective strengths to create a comprehensive decision-support framework. For instance, ML models like Random Forest can estimate the probabilities and impacts of delays, while MCDA techniques such as AHP rank delay factors based on their significance [14]. This integration ensures both predictive accuracy and actionable prioritization, allowing stakeholders to address critical delay factors proactively. Table 5 summarizes the roles of ML and MCDA in the integrated framework. Table 5 Integration of Ml and MCDA in Construction Delay Management.

Table 5 Integration of Ml and MCDA in Construction Delay Management

Component	Role
Machine Learning (ML)	Predicting delay impacts on cost, schedule, and quality.
MCDA	Prioritizing delay factors based on their influence on project outcomes.

6.2. Advantages

The hybrid ML-MCDA framework offers several advantages:

- Predictive Accuracy: ML models provide precise forecasts of delay impacts, enabling proactive planning.
- Structured Prioritization: MCDA methods ensure that critical delay
- factors are identified and ranked Systematically.
- Actionable Insights: By integrating predictions with prioritization, the framework delivers insights that support resource allocation and decision-making. [20]
- Enhanced Decision-Support: The combined approach allows for dynamic scenario analysis, helping stakeholders adapt to real-time project changes.

7. Future Directions

While the integration of ML and MCDA has demonstrated promise, several gaps remain that warrant further exploration. Table 6 summarizes these research gaps and proposed solutions. Future research should focus on creating interactive decision-support tools that integrate ML predictions with MCDA rankings for real-time construction delay management (Sahu et al., 2024). [21]

Table 6 Research Gaps and Proposed Solutions

Research Gap	Proposed Solution
Limited integration of ML and MCDA	Develop hybrid frameworks combining predictive and decision-support tools.
Lack of real-time applications	Design adaptive models leveraging real-time project data.
Limited scalability and generalizability	Create models tested across diverse geographic and project contexts.

Conclusion

This review highlights the transformative potential of integrating Machine Learning and Multi-Criteria Decision Analysis in construction delay management. ML provides predictive insights into delay impacts, while MCDA ensures structured prioritization of factors, creating a comprehensive framework that addresses the limitations of traditional methods. The development of hybrid frameworks and real-time decision-support tools will further enhance project performance, enabling stakeholders to mitigate delays proactively. Future advancements in this field are expected to bridge existing research gaps, foster scalability, and revolutionize construction project management through data-driven decision-making.

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