CHAPTER 144

To Study the Difficulties Faced by Organization in Managing Over-Allocated Resources

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ABSTRACT

In the construction industry, there are large challenges in resource allocation and project scheduling. Construction projects, generally associated with inefficiencies, cost overruns, and project delays, need methods more sophisticated than just the Critical Path Method (CPM) and Resource Leveling, which, although useful, tend to be quite inadequate to cope with complex workloads and uncertainties inherent in construction projects. The paper presents a novel approach to integrating artificial intelligence into traditional project management techniques to make better decisions to optimize resource usage. With Artificial Intelligence (AI) algorithms, the project manager would be able to achieve better accuracy in forecasters, effective adjustment in critical paths, and improve resource leveling to avoid risks of over allocation and bottlenecks. The study thus has put a lot of focus on the user-friendly interface between AI-driven insights and project managers for practical application in real-world scenarios. This paper provides a comprehensive analysis on the integration of AI into project management to provide a framework for improving project outcomes in terms of time, cost, and overall effectiveness, to improve construction management practices.

Keywords: Microsoft projects; PRIMAVERA; Resource management; Critical path method; Resource leveling.

1.0 Introduction

The construction industry is vital to global economic development, driving infrastructure growth and employment. However, inefficiencies in project scheduling and resource management persist, causing delays, cost overruns, and resource wastage. Traditional scheduling methods, such as the Critical Path Method (CPM) and Resource Leveling, rely on static assumptions and struggle to adapt to dynamic project conditions. Artificial Intelligence offers advanced capabilities in predictive analytics, optimization, and decision-making, addressing the limitations of traditional scheduling.

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AI-driven models enable real-time adaptability, improved forecasting, and optimized resource distribution, reducing human errors and enhancing efficiency. This research aims to improve construction project scheduling by integrating AI-driven solutions to optimize timelines, enhance resource allocation, and improve efficiency. It evaluates the limitations of traditional methods and explores AI-based models' practical applications in project management tools like Microsoft Project (MSP) and Primavera.

The study examines AI techniques such as predictive analytics, machine learning-based optimization, and automated decision-making for construction scheduling. It assesses AI model efficiency in resource allocation, timeline adjustments, and risk management while evaluating their integration feasibility with existing project management tools. Despite AI's potential, challenges include access to high-quality project data, computational demands, and stakeholder trust in AI-driven decision-making. Smaller firms may face integration and scalability issues due to limited technological resources. This paper analyzes traditional scheduling methods, AI advancements, and a proposed AI-based scheduling framework. It explores AI integration with MSP and Primavera and assesses its impact on project timelines, resource utilization, and cost efficiency. The study concludes with key findings, future research directions, and AI adoption implications in construction scheduling, bridging the gap between theoretical advancements and practical implementation for more efficient project management.

2.0 Literature Review

The construction industry is a crucial driver of economic development, contributing to infrastructure expansion and employment generation. However, inefficiencies in project scheduling and resource management continue to hinder project success, leading to delays, cost overruns, and wasted resources. Traditional scheduling techniques, such as the Critical Path Method (CPM) and Resource Leveling, rely on static assumptions that struggle to accommodate dynamic project conditions (Khan *et al.*, 2024). These methods lack flexibility, making them ineffective in responding to uncertainties such as weather disruptions, labor shortages, and supply chain delays. AI-driven approaches offer a solution by enhancing predictive analytics, optimization, and decision-making, enabling real-time adaptability and improved forecasting accuracy (Egwim *et al.*, 2022). This research investigates the potential of AI-driven solutions to optimize project timelines, resource allocation, and efficiency while evaluating their feasibility in project management tools like Microsoft Project (MSP) and Primavera.

Traditional scheduling methodologies have been widely utilized for decades. (Kelley, 1961) introduced the Critical Path Method (CPM), a technique that determines project timelines based on deterministic task durations and precedence relationships. While CPM is effective in identifying critical activities that directly influence project completion, it lacks the ability to accommodate real-time changes. This rigidity often results in scheduling inefficiencies when unforeseen disruptions occur. Similarly, the Program Evaluation and Review Technique (PERT)

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was developed to address project scheduling complexities by incorporating probabilistic time estimates. However, its reliance on estimated task durations still poses challenges in handling highly dynamic project environments. Shen *et al.* (2022) highlight that traditional scheduling methods, including CPM and PERT, struggle to adapt to uncertainties in construction projects. These techniques assume fixed task durations and static precedence relationships, which fail to capture real-world variations. Projects often experience unforeseen changes due to labor shortages, fluctuating material availability, and environmental factors, necessitating a more adaptive scheduling approach. This study emphasizes the need for AI-driven models that integrate real-time project data to optimize scheduling decisions dynamically.

Hegazy & Menesi (2010) examine the effectiveness of Resource Leveling, a scheduling technique designed to balance resource allocation across project activities. While Resource Leveling seeks to prevent resource overuse and inefficiencies, it frequently results in suboptimal scheduling decisions due to its inability to incorporate real-time project conditions. The authors argue that AI-based optimization models can address these limitations by continuously analyzing project constraints and adjusting schedules accordingly. Mayer (2002) discuss the impact of unexpected delays in construction projects. They identify factors such as adverse weather conditions, labor shortages, and supply chain disruptions as common causes of scheduling inefficiencies. Traditional methods like CPM and PERT fail to accommodate these uncertainties due to their static nature. The authors suggest that AI-powered predictive analytics can enhance scheduling accuracy by learning from historical project data and forecasting potential risks.

Johannsen (2021) argue that traditional scheduling methods are insufficient for managing probabilistic project elements. They note that CPM and PERT rely on fixed-duration task estimates, which do not reflect the inherent variability of construction activities. By leveraging machine learning and deep learning techniques, AI-driven scheduling frameworks can model uncertainties more effectively and provide adaptive scheduling recommendations. Egwin *et al.* (2022) explore the role of predictive analytics in construction scheduling. Their study demonstrates that AI models can analyze historical project data to predict potential delays and optimize resource allocation. AI-based forecasting techniques improve decision-making accuracy, enabling project managers to take proactive measures to mitigate scheduling risks. The authors conclude that integrating AI into project management tools like MSP and Primavera enhances real-time adaptability and scheduling efficiency.

Asghari *et al.* (2022) investigate the application of reinforcement learning in dynamic scheduling adjustments. Their research shows that AI models can continuously learn from evolving project conditions and refine scheduling strategies in real time. Reinforcement learning techniques allow AI-driven scheduling systems to adapt to unexpected changes, making them more effective than traditional static methods. Egbedian *et al.* (2021) analyze the impact of AI-driven scheduling frameworks on resource allocation accuracy and project completion times. Their study reveals that machine learning-based optimization techniques, such as genetic

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algorithms and neural networks, significantly improve scheduling efficiency. By automating the resource allocation process, AI reduces human errors and enhances overall project performance.

Khosrowshahi & Arayici (2012) discuss the integration of AI-based scheduling tools into construction project management software. They highlight the advantages of AI-driven models embedded in Primavera and MSP, including real-time adaptability and predictive insights. The authors argue that AI-enhanced scheduling tools offer superior performance compared to traditional methodologies by continuously analyzing project data and adjusting schedules accordingly. Regona *et al.* (2023) examine the challenges associated with AI adoption in construction scheduling. They identify data availability as a major barrier, as AI models require extensive historical project data for training. Many construction firms lack structured datasets, making it difficult to implement AI-driven scheduling solutions effectively. The authors recommend developing standardized data collection practices to facilitate AI integration in the industry. This study aims to bridge the gap between theoretical AI advancements and practical applications in construction scheduling. By analyzing traditional scheduling methods, AI innovations, and a proposed AI-based scheduling framework, it evaluates AI integration with MSP and Primavera. The research assesses AI's impact on project timelines, resource utilization, and cost efficiency, concluding with key findings, future research directions, and implications for AI adoption in construction scheduling.

3.0 Proposed Methodology

The Proposed Methodology focuses on integrating AI into construction scheduling to enhance efficiency and decision-making. It involves four main steps: data collection, AI model development, integration with scheduling software, and performance evaluation. Historical project data, including task durations and resource allocations, will be gathered and preprocessed to ensure accuracy. AI techniques, such as machine learning and optimization algorithms, will be used to predict project timelines and optimize scheduling. The AI system will be integrated with MSP and Primavera P6 using APIs (Application programming interface), plugins, or cloud-based solutions for real-time updates. Finally, the system's performance will be evaluated based on accuracy, efficiency, scalability, and usability, with comparisons to traditional scheduling methods and feedback from industry professionals to refine the model.

3.1 Data collection implementation

Data collection implementation involves various tools and techniques to extract structured and unstructured project data efficiently. SQL (Structured Query Language) queries are used to retrieve structured data such as task schedules and dependencies from relational databases like MS Project's SQL Server. APIs, such as those provided by Primavera P6 and MS Project, automate real-time data extraction, minimizing manual effort and enabling seamless integration with AI models. In cases where APIs are unavailable, web scraping tools like

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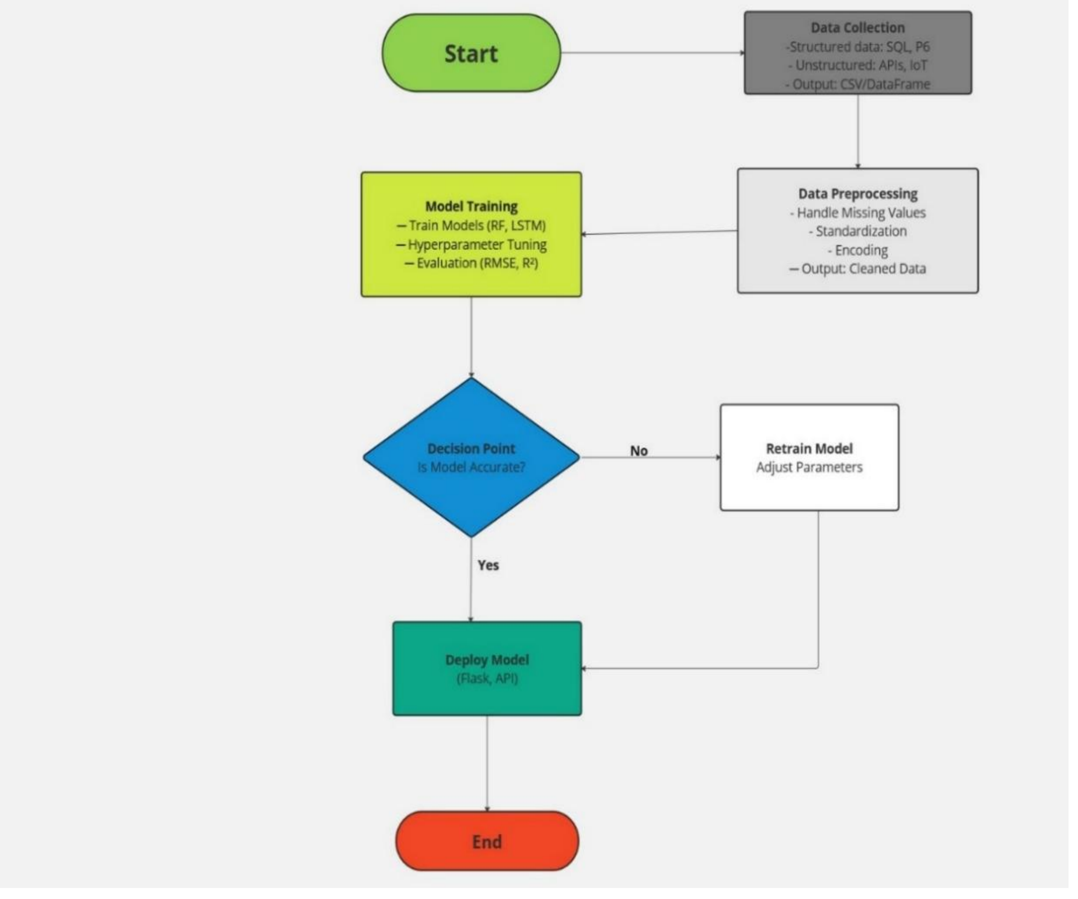
Python's BeautifulSoup and Selenium help extract project logs and reports. IoT sensors and edge computing technologies, including MQTT (Message Queuing Telemetry Transport) and AWS (Amazon Web Services) IoT (Internet of Things), facilitate real-time tracking of workforce efficiency and equipment availability, improving the accuracy of AI-driven analyses.

Figure 1: Flowchart of Implementation (Workflow Architecture)



The implementation of these methods involves using SQL queries to connect to databases, extract relevant project details, and store the data for machine learning processing. APIs require authentication, HTTP (Hypertext Transfer Protocol) requests, and data parsing to fetch and utilize project schedules. Similarly, web scraping involves retrieving raw HTML (Hypertext Markup Language) from webpages, extracting key information, and storing it for further analysis. These techniques collectively enhance data collection, ensuring accurate and real-time project monitoring and decision-making.

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3.2 Data preprocessing implementation

To preprocess and clean data effectively, several tools and techniques are used. Pandas, a popular Python library, helps in handling missing values, removing duplicate records, and formatting data properly. It allows users to easily manipulate large datasets by filling in missing values and ensuring consistency. NumPy is another essential library that specializes in performing complex numerical operations and calculations. It is highly efficient in processing large amounts of numerical data quickly, making it useful for data analysis. Scikit-learn, a machine learning library, provides various tools for data preprocessing. The Imputer function helps fill in missing values, ensuring that incomplete data does not cause errors in analysis. Standard-Scaler is used to normalize and standardize numeric data, making sure that all values are on a similar scale, which improves the performance of machine learning models. Label-Encoder converts categorical data into numerical values, allowing machine learning algorithms to process them efficiently. These tools work together to clean, organize, and transform raw data into a structured format that can be used for analysis and AI applications.

Table 1: Data Before Preprocessing

Task ID	Task Name	Task Duration	Task Cost ($)	Task Status	Task Dependencies
1	Task A	5 days	10000	InProgress	Task B, Task C
2	Task B	NaN	8000	Completed	Task A
3	Task C	7 days	10000	InProgress	Task B, Task C
4	Task D	10 days	NaN	Not Start	Task A

Table 2: Data After Preprocessing

Task ID	Task Name	Task Duration (scaled)	Task Cost ($) (imputed)	Task Status (encoded)	Task Complexity
1	Task A	0.7	10000	1	High
2	Task B	0.6	8000	0	Medium
3	Task C	1.0	9000 (mean)	2	Low

3.3 Model training implementation

To make accurate predictions in project management, different machine learning models are used based on the complexity of the data and forecasting requirements. Linear Regression (LR) is a simple, yet effective model used to predict task completion time. It works by analyzing past data and identifying relationships between task duration and influencing factors, making it useful for estimating timelines. Random Forest (RF) is a more advanced model that can handle complex project dependencies. Since construction and engineering projects involve multiple interdependent tasks, Random Forest considers various factors at once

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and predicts possible delays more accurately than simpler models. XGBoost is a powerful and optimized machine learning algorithm designed to improve accuracy in forecasting project duration. It works better than many traditional models because it efficiently processes large, structured datasets and minimizes errors. Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), is used for analyzing time-series data, meaning it can learn from past project trends to predict future outcomes. This is particularly useful in identifying sequential dependencies, such as how previous project delays might affect upcoming tasks. Together, these models help project managers make better decisions by predicting risks, estimating completion times, and optimizing schedules based on historical data.

3.4 Integration with scheduling software

The integration of AI models with scheduling software like Microsoft Project or Primavera P6 enhances real-time decision-making and dynamic scheduling. This process involves API-based integration, plugin development, and cloud-based synchronization to create a seamless connection between AI systems and project management tools. API-based integration starts with authenticating with scheduling software using credentials like OAuth (Open Authorization) tokens, followed by retrieving project data through HTTP GET requests to access schedules, task dependencies, and resource allocations. AI-generated insights, such as optimized schedules and risk alerts, are then sent back via HTTP POST requests, allowing automatic updates to project schedules based on AI-driven predictions.

Another approach involves developing custom plugins that embed AI functionalities directly into MSP or Primavera P6. This process requires designing an intuitive user interface to display AI insights, ensuring real-time data retrieval from the AI system, and dynamically updating project schedules based on AI recommendations. Cloud-based integration further enhances scalability by deploying AI models on platforms like AWS, Azure, or Google Cloud, with secure data transfer via HTTPS or MQTT protocols. Real-time synchronization ensures that any updates in the scheduling software reflect AI-driven adjustments. Additionally, AI-powered data visualization and reporting tools, such as Tableau and Power BI, help generate insights through Gantt charts and resource heat-maps. Customizable reports highlight key project metrics, including predicted completion dates, resource utilization, and risk assessments, with export options in formats like PDF and Excel for stakeholder presentations. Integrating AI with scheduling software significantly improves efficiency by enhancing forecasting accuracy, optimizing resource allocation, and minimizing project risks, making it a crucial advancement in construction project management.

4.0 Result and Performance Evaluation

Evaluating the AI-integrated system ensures its effectiveness in construction project management. Key metrics include accuracy, efficiency, usability, and scalability. Accuracy

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measures AI predictions against actual outcomes, while efficiency assesses reductions in delays and costs. Usability evaluates user satisfaction, and scalability tests performance on large projects. Comparative analysis benchmarks AI against traditional scheduling methods like Critical Path Method and Resource Leveling to quantify improvements. Simulation and testing validate adaptability by analyzing AI responses to real-world scenarios like delays and resource shortages. The system's ability to dynamically adjust schedules is assessed. User feedback from project managers helps refine AI models, focusing on visualization and processing speed improvements. Performance reports summarize key metrics, comparative analysis, and user feedback, demonstrating AI's benefits and justifying further investment.

5.0 Recommendations and Future Scope

In order to enhance forecasts for project schedules and resource allocation, future research in AI-driven construction scheduling should focus on boosting the accuracy of machine learning models by using larger and more diverse datasets. Real-time data collecting, decision-making, and transparency can be further improved by integrating AI with innovative technologies like blockchain, the Internet of Things (IoT), and Building Information Modeling (BIM). It's also critical to make AI-integrated scheduling tools more user-friendly so that construction industry experts easily understand and utilize AI-generated insights. Implementation issues will be resolved with additional validation through pilot projects and real-world case studies, which will offer useful insights into the efficacy of AI-driven scheduling. Future studies should also look into ethical and regulatory issues to make ensure AI solutions satisfy industry requirements.

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