The Role of Artificial Intelligence in Optimizing Resource Allocation in Engineering Projects in Libya

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Abstract:

Resource allocation is the bedrock of a successful engineering project management, with respect to effective usage of resources like labor, materials, and equipment. The traditional methods that depend on static optimization and heuristic techniques are restricted in their adaptability to real-time changes and result in inefficiencies, cost overruns, and missed deadlines. These factors are increasingly necessary as modern engineering projects become complex and large in scale. This research goes beyond the issues outlined above, instead proposing a fully AI-driven framework to better allocate resources to bring about vastly improved project outcomes. While traditional techniques will rely solely on predictive analytics and advanced algorithms using machine learning techniques to evaluate immense amounts of both historical and real-time data in order to create accurate demand for resources as well as to do dynamic re-allocations. The proposed framework as illustrated in the case study performed in Libya, can minimize resource wastage, enhance productivity, and respond to unforeseen disruptions such as supply chain interruptions or labor shortages by integrating these capabilities with optimization algorithms. The novelty in this approach is the integration of predictive analytics with real-time decision-making within the constraint framework of meeting budgetary and timeline limits without compromise to efficiency or quality. The study aims to design and validate a robust resource allocation model for the purpose of forecasting an accuracy of 99.3% and optimizing resource utilization. This study follows a hybrid AI system, where predictive analytics are generating the forecast regarding demands on resources and optimization algorithms dynamically allocating them. Simulations and case studies demonstrate that the proposed framework does reduce idle time, minimize costs, and ensure timely project completion. The results obtained show tremendous potential for AI-driven systems in shifting the paradigm of engineering resource management.

Keywords: Artificial Intelligence, Efficiency, Optimization, Predictive Analytics, Resource Allocation.

الملخص:

يُعدّ تخصيص الموارد الركيزة الأساسية لنجاح إدارة المشاريع الهندسية، وذلك من خلال الاستخدام الفعّال للموارد مثل العمالة والمواد والمعدات. إلا أنّ الأساليب التقليدية المعتمدة على النمذجة الثابتة وتقنيات التحسين القائمة على الإجراءات الحدسية تعاني من محدودية في قدرتها على التكيف مع التغيرات الفورية، مما يؤدي إلى انخفاض الكفاءة، وتجاوز التكاليف، وتفويت المواعيد النهائية. وتزداد أهمية هذه التحديات مع تزايد تعقيد المشاريع الهندسية الحديثة واتساع نطاقها. يتجاوز هذا البحث المشكلات السابقة من خلال اقتراح إطار عمل متكامل قائم كليًّا على الذكاء الاصطناعي بهدف تحسين تخصيص الموارد وتحقيق نتائج أفضل للمشاريع. وعلى عكس الأساليب التقليدية، يعتمد الإطار المقترح على التحليلات التنبؤية والخوارزميات المتقدمة باستخدام تقنيات التعلّم الآلي لتحليل كميات هائلة من البيانات التاريخية واللحظية، بهدف التنبؤ بدقة بالاحتياجات المستقبلية للموارد وتنفيذ عمليات إعادة تخصيص ديناميكية. وكما توضّح دراسة الحالة التي أُجريت في ليبيا، يَملك الإطار المقترح القدرة على تقليل الهدر في الموارد، وتعزيز الإنتاجية، والتعامل مع الاضطرابات غير المتوقعة مثل تعطّل سلاسل الإمداد أو نقص العمالة، وذلك من خلال دمج التحليلات التنبؤية مع خوارزميات التحسين. وتكمن حداثة هذا النهج في الجمع بين التحليلات التنبؤية واتخاذ القرار الفوري ضمن إطار مُقيَّد يضمن الالتزام بالميزانية والجدول الزمني دون المساس بالكفاءة أو الجودة. يهدف البحث إلى تصميم نموذج قوي لتخصيص الموارد والتحقق من فعاليته، مع تحقيق دقة تنبؤ تصل إلى 99.3% وتحسين استغلال الموارد بشكل أمثل. ويقوم هذا النموذج على نظام هجين للذكاء الاصطناعي، حيث تتولى التحليلات التنبؤية تقدير الطلب على الموارد، بينما تقوم خوارزميات التحسين بتوزيعها بشكل ديناميكي. وتُظهر عمليات المحاكاة ودراسات الحالة أن الإطار المقترح يساهم في تقليل وقت الخمول، وخفض التكاليف، وضمان إنجاز المشاريع في الوقت المحدد. وتشير النتائج إلى الإمكانات الكبيرة للأنظمة المعتمدة على الذكاء الاصطناعي في إحداث نقلة نوعية في إدارة الموارد الهندسية.

الكلمات المفتاحية: التحسين، التحليلات التنبؤية، تخصيص الموارد، الذكاء الاصطناعي، الكفاءة.

1. Introduction

Resource allocation is considered to be an integral part of the successful realization of engineering projects where tasks, budgets, people, and resources are managed well for the execution of the objectives under the predefined constraints [1]. On the other hand, the advancement of modern-day engineering activities increases complexity and magnitudes, resulting in the vulnerabilities of traditional techniques that are heavily reliant on planning techniques or simple heuristic methods [2]. These approaches usually fail to cope well with real-time requirements of the projects, creating inefficiencies, delays, and cost overruns that negatively affect project success[3].

Artificial Intelligence (AI) is redefining the way resources are allocated, presenting advanced tools and techniques that could handle complex decision-making processes [4]. AI algorithms have the ability to analyze large quantities of data that would identify ideal allocation strategies as well as the forecast of resources in demand for the future period [5], [6]. By infusing predictive analytics, machine learning, and optimization algorithms, AI allows project managers to allocate their resources more efficiently, thereby lessening waste and increasing productivity [7], [8], [9]. AI systems can also accommodate unforeseen issues, such as supply chain interruptions or workforce shifts, by rebalancing resource plans in real time, as in Figure 1.

Engineering project applications have tremendous potential in AI to increase efficiency and better outcome delivery [10]. With AI, a competitive advantage has been developed regarding the reduction of material waste to the optimal use of labour schedule and on-time delivery [11], [12]. In this paper, the methodology behind AI for the allocation of resources in engineering projects is examined. The paper provides an understanding of the methodologies applied, benefits received, and what the future might hold for the management of engineering projects.

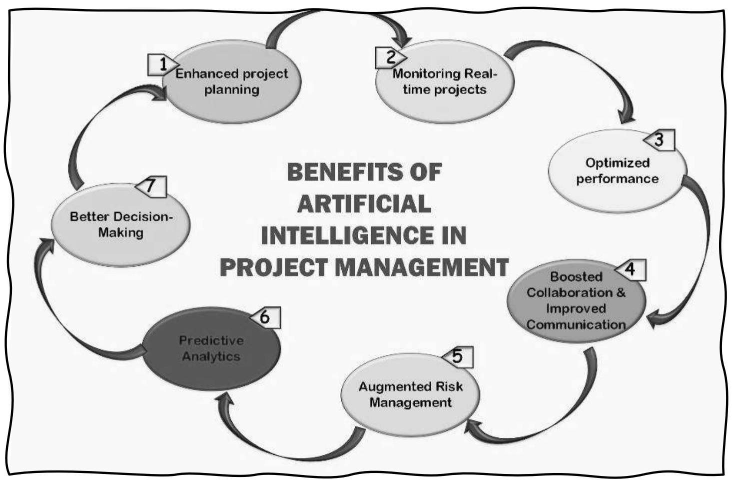

Figure (1): AI-driven approaches to project management

1.1. Problem Statement:

In engineering projects, inefficient resource allocation has long been a huge problem and often results in poor performance, budget invades, and delays [13]. Traditional approaches strongly rely on the plans and static optimization techniques since the resource allocation approaches would not adapt to the dynamic characteristics of modern engineering tasks [14]. With these constraints, as projects get larger, more resources go wasted, operational inefficiencies arise, and deadlines are missed [15]. This necessitates innovative solutions that can respond to changing conditions in the project and ensure efficient use of resources [16].

1.2. Research Motivation:

The integration of Artificial Intelligence in the management of engineering projects holds the promise to be a panacea for the old problems of resource allocation [17]. It can revolutionize project management through the handling of large data, prediction of the demand for resources, and dynamic optimization of the distribution of resources. This research is motivated by the desire to explore the possibilities of using AI to improve efficiency, reduce waste, and minimize risks in complex engineering environments. Data-driven decisions in the project will enhance the outcome and help in bridging the limitations of traditional methods by using AI.

1.3. Research Objective:

1. Discuss the role of AI in optimizing resource allocation for engineering projects.
2. Identify efficient techniques for AI techniques and their potential applications in reality.
3. Give actionable insights for better decision-making and more efficient projects.
4. Predictive analytics resource needs.
5. Design resource allocation models optimizing resources allocation without violating the constraints of budgets and operation, and consider integrating AI-based solution in actual projects workflows.

1.4. Research Contribution:

1. Extensive review of the AI-driven methodology for resource allocation in engineering projects.
2. Suggestion of a visionary framework for bringing AI into Project Management.
3. Assessment through simulations or case studies on AI's efficiency.
4. Identification of the adoption challenges and limitations, and recommendation for future research and practical implementation.
5. This would bridge the gap between theoretically advancing AI and actually applying it practically in engineering project management.

This study presents the application of AI-driven methodologies for engineering project resource optimization. Section 1 discusses introduction of the inefficiencies and shortcomings of traditional methods of resource allocation, including static planning and heuristic techniques, which fail to adapt to the dynamic requirements of the project. Section 2 reviews work on the advancement in AI technologies relating to predictive analytics and optimization algorithms which would mitigate this shortcoming. Section 3 shows the proposed method, which comprises predictive analytics techniques for forecasting and optimization algorithms techniques for real time dynamic allocation. Section 4 presents an Evaluation of the approach, performance in comparison with those of conventional techniques; Section 5 concludes with discussion on the possible impact of the AI revolutionized resource management and opens up future scopes of research.

2. Related Works:

Ruchit Parekh and Olivia Mitchell [18] provided in-depth review techniques on how to transform resource-allocation processes by using AI for machine learning, optimization algorithms. Focusing mainly on scheduling and estimation of cost through the research carried out, there is evidence showing that AI methods improve the accuracy of resource allocation and enhance overall project efficiency. These methodologies help project managers identify best strategies, reduce waste, and adapt to dynamic requirements in the projects. The study, however, is dominated by several serious challenges, particularly in the training of AI models, where access to quality data can influence the kind of data provided. Inability to generalize is also common because of the absence of good datasets in most cases. Scaling AI solutions to larger and more complex projects still remains a limitation for the computational demand and integration complexity. The study highlighted the need for more robust and scalable data collection frameworks for the full potential of AI to be realized in project management.

Soleymani, Bonyani, and Attarzadeh [19] investigated based on the scope of applying artificial intelligence techniques into resource allocation of engineering projects and, therefore applies machine learning techniques and optimization algorithms. In applying tasks like scheduling and cost estimations, AI-driven approached enhance a project's effectiveness and increase resource distribution accuracy considerably. These methods assist project managers in identifying the optimal strategies, waste minimization, and dynamic requirements of a project. However, the study underlined the following significant challenges: in the training phase of AI models, availability and quality of data are highly crucial. Moreover, AI solutions to scale larger and complex projects pose computational and integration-related challenges. This is yet another limitation and underscores the requirement of having even stronger and more scalable data gathering frameworks for making better use of AI in managing projects.

Kumar and Gore [20] evaluated whether artificial intelligence can be applied to the management of resources as well as performance optimization in software systems. A performance comparison of three mainstream AI techniques, namely reinforcement learning, neural networks, and genetic algorithms, on the following parameters—resource utilization, average response time, throughput, costs, prediction capability, stability, and convergence time—is considered in the study. The findings show that the neural networks were the best for acquiring resources and the response rates. Reinforcement learning was competitive in its performance, whereas genetic algorithms presented a good approach in some contexts. The paper does acknowledge some of the issues in scaling up these AI approaches to larger applications with more varied usage patterns. Findings: This paper calls for scalable AI approaches to be applied in managing software resources effectively within dynamic environments.

Ferrera [21] explored the Impact of Artificial Intelligence on Project Management Across the Manufacturing, Technology, and Construction Industries by this author is a comprehensive investigation of how AI influences the management of projects in diverse sectors. It attempts to analyze what benefits, drawbacks, and consequences AI would eventually entail for such sectors. Key findings also show that it is mainly about automating work and enhancing function areas such as brainstorming and communication, so efficiency and, by extension, team productivity really increase. Thus, the article points out, although AI generally brings much positive impact, there are always challenges associated with its implementation: robust data collection frameworks and potentially complex integration. These findings indicate that challenges must be overcome to fully leverage the benefits of AI in project management, and a strategic approach to the integration of AI is necessary for overcoming these barriers.

In Transforming Project Management with AI: Opportunities and Challenges, the Yadav [22] introduced a systematic discussion on the opportunities and challenges offered by AI-based techniques in the realm of project management. Such study identifies some AI applications enhancing the processes for scheduling, risk assessment, resource allocation, etc., and mentions benefits such as increased efficiency and accuracy and better capabilities in decision making. The research also discussed the challenges with AI implementation such as data privacy, specialized skill requirements, and resistance to organizational change. The authors propose that there is a need for a strategic approach in managing these challenges properly through training, change management, and investment in technology. The findings of the research conclude that the opportunities offered by AI are highly significant, but the successful integration into the project management practice requires careful consideration of these challenges.

Nicholas Dacre, Dacre, and Kockum [23] furnished new enlightenment on the nature of artificial intelligence in project management. The study examined the extant applications in the field. It discussed at length the nature of AI potentials to transform praxis in handling projects. To this end, it underlined the utility in the automation of routine tasks or operations, enrichment of decisional processes, as well as perfecting project performances. The study provided future implications, indicating that AI might make management processes more efficient. However, this is challenged by such factors as the limitation of access to skilled professionals who would manage the AI tools and how data quality plays a great role in the effective implementation of AI in project management. This suggests that further research, towards overcoming these challenges, would be necessary in order to fully exploit its capabilities in project management.

Joloudari et al. [24] conversed the application of AI methods in resource allocation across different computing paradigms, such as cloud computing, Internet of Things (IoT), and 5G networks. The authors divide the resource allocation approaches into two categories: auction-based and optimization-based methods. The latter uses AI techniques such as deep learning, reinforcement learning, and Bayesian learning. The study has thoroughly portrayed how AI can streamline resource allocation, thereby increase efficiency and save costs in various computing environments. To this end, the paper identifies challenges; amongst which are high-quality data and complexities involved in implementing AI solutions across different platforms. From the findings, it was revealed that with such great advantages of AI, solving such problems is essential for effective management of resources. The analysis argues for further research in developing robust AI models that suit specific computing paradigms.

Egbedion [25] worked on integration in project management by the usage of artificial intelligence with respect to augmenting the effectiveness of the outputs. Project management has become more essential for a project's information system successfully. Non-adoption of artificial intelligence adopters has often, scheduling and allocating resources that faced difficulties of the complex, dynamic changes, as well as the uncertain nature. The study explores how AI can help deal with these challenges by offering more efficient and adaptive strategies for scheduling and resource allocation. Authors make a case study to show how AI techniques can be of practical relevance in real-world project cases. The result of the study indicates that AI-driven approaches lead to improved project performance and better management of resources. The study also focused on how AI can alter the conventional traditional project management processes by providing effective solutions to issues that are very common.

Several researches have been conducted on AI in project management: some of them dealt with issues regarding resource allocations, scheduling, cost estimations, and general efficiency optimization. Techniques applied include machine learning, optimization algorithms, neural networks, reinforcement learning, and genetic algorithms. It has been widely emphasized that AI aids in automating routine tasks, optimizing resource usage, and adapting dynamically to changing project requirements across industries such as manufacturing, technology, and engineering. Common limitations include the demand for quality data, scaling AI solutions in large projects, and complications of computational and integration complexity along with a shortage of proper experts and technicians to manage these AI tools. Issues of data privacy, resistance to change in organizations, and lack of strong frameworks all act as a barrier to the effective implementation. However, studies together emphasize the need for scalable, adaptable AI models and strategic approaches to make the most out of AI in project management.

3. Methodology: AI-Driven Predictive Analytics and Optimization Framework for Efficient Resource Management in Construction Projects

This methodology addresses the challenges of resource management in construction projects by combining predictive analytics and optimization techniques. It starts from identifying material delays, misestimating of resources, and inefficiencies, leading to project delay and cost overruns. The model predicts labor hours, material needs, and equipment usage by applying multivariate linear regression to historical, real-time, and external data. Balancing these, the optimization model of genetic algorithms provides resource allocation without compromising constraints, such as budgets, availability of resources, and dependencies on phase, ensuring efficiency, as depicted in Figure 2. Validating metrics, including MAE and RMSE, will be followed with real-time monitoring via dashboards during implementation to further iteratively adjust, resulting in streamlining resource utilization for better project outcomes.

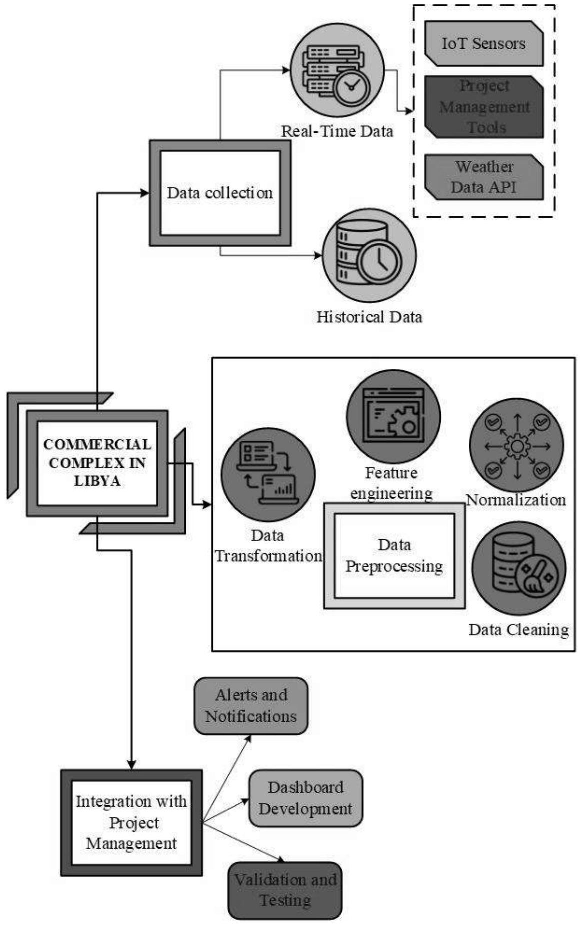

Figure (2): Overall Methodology Framework

3.1. Case Study: Engineering Project in Libya

The research aims to optimize resource allocation for large-scale construction projects, with the prime focus area currently being the Commercial complex in Libya. One of the examples is a D.L1,650-crore commercial project where a 50-story building is to be constructed within a time frame of 24 months. Civil engineering and project management have been merged with artificial intelligence such that machine learning computes its predictive model and the optimization of resource utilization. The two primary data sources for this research are: historical project records and real-time monitoring systems. Historical data describes the patterns developed in resource utilization, delays, and cost overrun, which in turn form a basis for developing predictive models. Simultaneously, IoT sensors and project management software enable current tracking of the consumption of materials, machinery use, labor application, and even the progress on the project site. This dual-layered approach towards data collection helps enhance predictive analytics and optimization models, ensuring the least amount of resource wastage, idle time, and a strict adherence to project timelines and budgets. Findings are supposed to be action-oriented and scalable, improving frameworks for decision-making in resource management in engineering and construction, with a focus on large-scale infrastructure development in, Libya.

3.2. Data collection

Data collection will include both historical insight and real-time monitoring to help analyse and develop the model for the Commercial complex in Libya. From other large construction projects, it was possible to obtain historical data related to the large projects, providing some records of the resource allocation, cost overruns, delay occurrences, and outcomes of the project. These data sets serve as a base for the training of predictive models for material usage, trends in labor allocation, and general project progression, as shown in Table 1. IoT sensors also capture real-time data about equipment operation, material consumption, and other activities at the site. Project management software tracks labor deployment and monitors day-to-day progress while indicating any deviation from the main schedule of the project. The model will be more accurate if there is integration of static historical data and dynamic real-time inputs into the resource demands and optimization strategies in modeling, thereby ensuring efficiency and sustainability in the development of the Commercial complex in Libya.

Table (1): Data Sources and Types

Data Source	Type of Data	Frequency of Collection	Purpose
Historical Project Records	Resource usage, delays, outcomes	One-time extraction	Training predictive models
IoT Sensors	Material consumption, machinery	Real-time monitoring	Real-time updates for dynamic analysis
Project Management Tools	Labor allocation, progress	Daily updates	Tracking deviations and adjustments
Weather Data API	Weather conditions	Weekly updates	Analyzing external environmental factors

3.3. Data Preprocessing

Data preprocessing is the critical step to prepare the dataset for the machine learning model so that accuracy, consistency, and relevance are assured. For this project, the following steps were followed in pre-processing historical and real-time data.

3.3.1. Data Cleaning

Handling Missing Values: Data gaps give a misplaced view of the population and can decrease model fitness. Mean imputation is used for numeric data and mode imputation is applied to categorical data.

Mean Imputation for Numeric Data is expressed in Eqn. (1).

$$x_{imputed} = \frac{\sum x_i}{n} \qquad (1)$$

Where, x_i are the observed data values, n is the number of observations taken.

Mode Imputation for Nominal Data: Missing values are replaced by the most frequently occurring value, that is, mode.

Outlier Detection and Deletion: The Interquartile Range (IQR) method was used to detect outliers which is represented in the Eqn. (2).

$$IQR = Q3 - Q1 \qquad (2)$$

3.3.2. Data Transformation

Standardization of units: Units are standardized to some common unit, since there are varying units for one and the same variable (eg material usage 'in kg versus tons').

Example: Material usage in kilograms.

Encoding Categorical Variables: One-hot encoding was used to transform categorical variables.

One-hot encoding is the formula used in categorical variables in the process. It describes how categorical data is encoded as a binary matrix, where each category is represented with its own single feature with either 0 or 1 value.

Specifically, to a given categorical variable with k unique categories:

- In the case where any of the categories are present, they are encoded as 1.
- If the category is missing, the data is coded as 0.

Example: Let the variable type be Categorical variable with variable name as Weather condition and the categories in it are: Sunny, Rainy and Cloudy, which is represented in Table 2.

Table (2): Example for Weather Conditions

Weather Condition	Sunny	Rainy	Cloudy
Sunny	1	0	0
Rainy	0	1	0
Cloudy	0	0	1

3.3.3. Feature Engineering

Feature engineering, more specifically one-hot encoding, means that categorical variables are converted to binary. This approach has been to allot an independent binary feature for every category in the categorical variable where 1 indicates a present category, while 0 reflects its absence. For instance, this encoding occurs by using categorical variable "Weather Condition" such that it encompasses different values in this variable; like "Sunny," "Rainy," and "Cloudy" being respectively encoded into [1, 0, 0], [0, 1, 0] as well as [0, 0, 1]. This transformation enables the machine learning models to process categorical data better, as they can be treated as numerical features. This improves model accuracy and interpretability.

Resource Utilization Rate: A new index has been deployed in order to measure the effectiveness of resource usage is in Eqn. (3).

$$\text{Utilization Rate} = \frac{\text{Active Resource Time}}{\text{Total Available Time}} \quad (3)$$

Idle Time Ratio: Measures the proportion of wasted time to scheduled time, providing insights into resources wastage. This represents idle time in Eqn. (4).

$$Idle\ Time\ ratio = \frac{Idle\ Time}{Total\ Scheduled\ Time} \quad (4)$$

Phase-Specific Metrics: Apart from that, historical data was pre-divided by construction phases such as the foundation phase, the structural phase, etc., this is because to have as many significant factors as possible to define the model required

3.3.4. Normalization

Normalization, with the most commonly used Min-Max scaling transforms numerical features into a common range of 0 to 1, is measured by using the Eqn. (5). It will rescale all values to adjust between their minimum and maximum so that one feature is not overwhelming the model by having extremely high and low values.

$$\acute{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

Here, $\acute{x}$ is the feature which is normalized, x_{max}, x_{min} means the lowest and the highest value of the feature.

These preprocessing steps made sure the dataset was clean and consistent for developing models that accurately enhance the allocation of resources and management of projects.

3.4. Identification of Challenges

1. ***Material Delays***
   - Material delays of important materials such as concrete or steel delay labor and machinery, hence cost the project but with no useful output.
   - Machinery hires expenses rise as the scheduled machinery like cranes or excavators do not work because the materials have not arrived.
2. ***Incorrect Estimation or Underestimation of Resources:***
   - Estimating incorrect labor hours or material quantities for certain phases waste resources or leads to shortages
   - Impact the following sequential phases, thus delaying project timelines and cost escalation.
3. ***Inefficient Use of Resources***
   - Skilled manpower is utilized on low-skill tasks or highly expensive machinery inappropriately and thus wastes the resources.
   - Extremely costly to the projects where the budget has been tightly placed.
4. ***Idle Labor and Machinery Costs:***
   - This compounded with idle labor and equipment increases overhead expenses without any corresponding gain.
   - Idle labor cost formula in shown in Eqn. (6).

$$\text{Idle Labor Cost} = \text{N} \times \text{H} \times \text{W} \tag{6}$$

Where, number of workers is N, idle hours= H, W=hour of wages.

5. ***Sequential Dependence Risks:***
   - One delay, for example in foundation work, cascades into subsequent dependencies of construction or finishing operations that will result in more inefficiency.
6. ***Budget Overruns from Inadequate Planning***
   - A good plan should take variability in supply for materials, labor availability, and machinery use into account and stop having unplanned expense.
7. ***Lack of Predictive Insight***
   - Unlike the traditional approaches, adequate AI-based advanced forecasting and optimization will be needed to predict the shifting trend of resource uses.

These problems emphasize the need for AI-based solutions, like regression models for resource forecasting and genetic algorithms for optimization, which will increase efficiency and decrease costs.

The Figure 3 represents the optimization of a project management structure by overcoming drawbacks such as delayed materials, low resource utilization, idle labourers, and increased budgets. A predictive analysis approach and a genetic algorithm-based model for validation and testing are used for validation and testing. The whole process involves various inputs such as historical data, real-time data, and variables from the environment, which employ multivariate linear regression to achieve better predictive capability and efficient management of the projects.

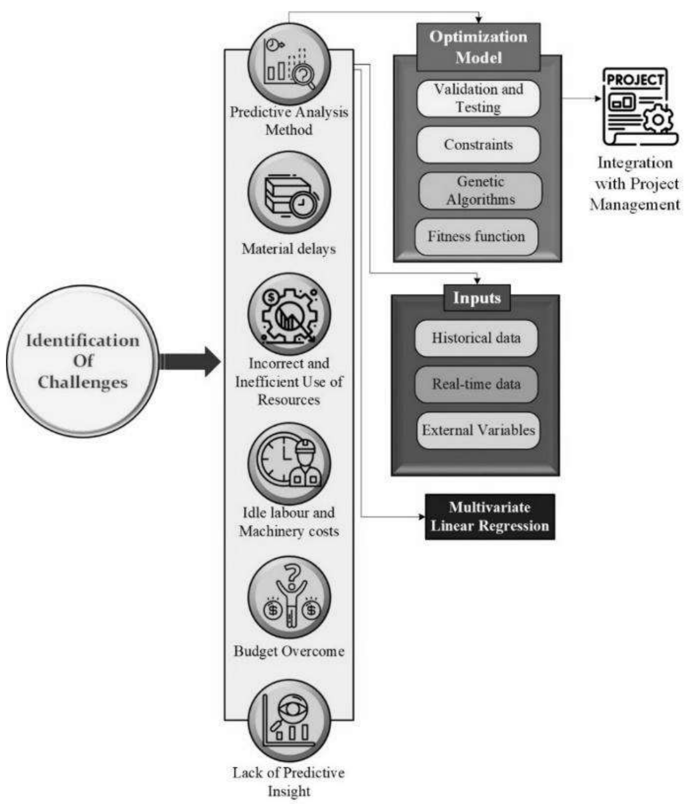

Figure (3): Project Optimization Framework Using Predictive Analysis

3.5. Development of Predictive Analytics Model

To precisely predict labor hours and material consumption at every stage of construction based on historical and real-time data.

3.5.1. Inputs

- **Historical Data:** This is any record of past construction projects and their usage, weather conditions, and progress metrics.
- **Real-time data:** Real-time tracking of project progress, equipment utilization, and extraneous inputs, such as weather.
- **External Variables:** Weather patterns, project deadlines, and budget constraints.

3.5.2. Multivariate Linear Regression for Resource Prediction

The Multivariate Linear Regression model acts as a base for forecasting labor hours, quantities of materials, and equipment use in different stages of construction. MLR is employed in order to estimate the necessary resources for the subsequent stages of the project, for example, the number of hours required for manpower and quantity of materials necessary. It also makes planning and disbursement easier so that there is reduced wastage and time consumption.

This technique has been very successful in modeling the interrelation between two or more independent variables (like weather, phase of construction, type of material) and a dependent variable, such as the number of labor hours needed. The general equation for MLR is in Eqn. (7).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \qquad (7)$$

Where, Y is the dependent variable, independent variables are X_1, X_2. ϵ is the variable error term. β_0 is the intercept term. β_n are terms which quantify impact of each predictor variable.

The Table 3 lists the relationship of construction phases and weather conditions along with material and labor hours requirements. This data feeds into training the predictive model that would forecast the resources used.

Table (3): Input Variables and Corresponding Resource Requirements Across Phases

Phase	Weather Condition (X_1)	Material Needs (X_2)	Labor Hours (Y)
Foundation	Sunny (1)	500 kg steel	520 hours
Structural	Rainy (0)	800 kg concrete	750 hours
Finishing	Cloudy (1)	300 paint	380 hours

3.6. Development of Optimization Model

To control time, money, human resource, equipment and all other resources in the most optimal manner to meet the time constraints of a project while at the same time keeping costs down.

3.6.1. Constraints

- **Budget Constraints:** Resource allocation for every construction phase should not exceed pre-defined budget limits.
- **Labor and Machinery Availability:** Allocate the availability of skilled and unskilled labor, along with the machines, like cranes and excavators.
- **Phase Dependencies:** The dependencies between phases are sequential, for example, foundation must be completed before structural work.

3.6.2. Genetic Algorithms (GA)

This project utilizes the powerful optimization technique of Genetic Algorithms (GA), which helps optimize resource allocation strategies iteratively. Inspired by natural selection principles, GA generates a population of candidate solutions in which each candidate is a particular plan for resource allocation. Solutions are then ranked through a fitness function that evaluates each candidate according to criteria such as cost efficiency, resource utilization, and compliance with project deadlines. For example, the fitness function can be given as a weighted sum of these parameters to rank the solutions in terms of their effectiveness. Best solutions are chosen for reproduction by crossover, combining their characteristics, and mutation for introducing small variations to explore additional possibilities. The process continues with multiple generations till an optimal or near-optimal solution is reached, as in Figure 4. GA is especially well-suited for this problem because it can handle complex constraints such as budget limits, resource availability, and phase dependencies to ensure an efficient allocation strategy that minimizes costs and meets deadlines effectively.

The optimization fitness function can be represented in the Eqn. (8).

$$\text{Fitness} = \frac{1}{1+\text{cost}} \times (1 - \text{Completion Time}) \qquad (8)$$

Were,

- Expenses represent the cost which is the total amount of money spent on acquisition of the resources.
- Completion Time is the time consumed in finishing this phase.

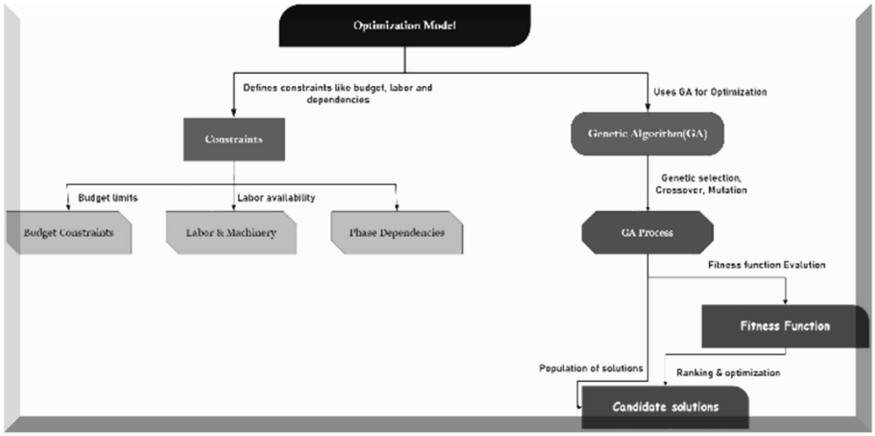

Figure (4): Optimization Model

3.7. Integration with Project Management

The project management integrated into AI-driven resource allocation comes from the necessity to create an encompassing graphical user interface visual of real-time prediction and distribution insight into AI-based resource resources for the support project managers obtain and make efficient critical decision-making toward finding potential problematic spots.

3.7.1. Dashboard Development

Dashboard is the central location to monitor how resources are utilized and allocated over the course of the project. The dashboard uses dynamic displays in order to illustrate resource utilization using graphs, from which material intake, machinery consumption, and deployment of labor may be easily identified. Key Features of the dashboard:

- **Resource Usage Visualization:** Graphs show daily, weekly, or monthly resource utilization. This enables easy identification of trends and discrepancies.
- **Resource Allocation Insights:** It will provide the distribution of resources across the project phases and thus identify overused or underutilized resources.
- **Progress Monitoring:** Instant updates on each milestone and project phase ensure a manager is conscious of the progress and any differences from the initial project schedule.

3.7.2. Alerts and Notifications

Automated alerts and notifications are built into the system for proactive management of project risks. Such notifications warn project managers if a shortage or delay is possible in certain stages of the project. The machine learning models analyze historical and real-time data to predict potential risks. For instance,

- **Shortage Alerts:** Whenever the material usage goes beyond pre-set thresholds or labor availability is less than required, it sends out the alerts.
- **Delay Notifications:** The deviation from the timeline is notified to the project manager, who can intervene and reallocate resources based on the requirements.

These features enhance the early detection and mitigation of risks for smoother project execution and better resource management. Project managers can then maintain better control over the project, ensuring efficient use of resources and adherence to deadlines.

3.8. Implementation and Monitoring

The last stage of the AI implementation and monitor stage is an effective way of ensuring that the models developed are implemented in the Commercial complex in Libya project. After the pilot phase of the construction project and after fine-tuning of AI models, it is done gradually – from the initial and the structural phases and only then for all phases of construction.

3.8.1. Pilot Phase

In the pilot phase, the AI models will be implemented on the foundational and structural work phases of the Commercial complex in Libya project. It is during these phases that some critical milestones for the overall construction process are experienced. Focusing on these phases will allow testing the models in controlled conditions, giving a comprehensive judgment of their performance before widespread usage.

In this stage, AI models predict the utilization of resources for labor, machinery, and material usage in the execution of work items such as excavation, laying foundations, and structural framing. These predictions are continuously monitored and compared with the actual usage of resources. This is to ensure that the model provides the necessary insights into the resource needs and minimizes the costs and the time required for the project execution.

3.8.2. Monitoring and Adjustments

The model's performance is evaluated by gathering real-time resource usage data from IoT sensors, machinery logs, and project management tools. This data includes metrics such as labor hours, material consumption, and machinery operation, which are then compared to AI predictions to detect discrepancies.

For example, in case the volume of concrete usage forecasted by the model is surpassed, adjustments are done. Such adjustments may include improving procurement processes, reassigning labor, or realigning machinery towards more efficient operation to meet project needs.

Continuous monitoring makes it possible for iterative improvements on the AI models. When such discrepancies are spotted, feedback loops get established, allowing predictions to get refined with the help of real-time data and so improve the future forecasts.

Table (4): Resource Comparison – Predicted vs. Actual

Phase	Predicted Material Usage (kg)	Actual Material Usage (kg)	Discrepancy (%)
Foundation	15,000	18,000	20% higher
Structural	25,000	23,000	8% lower

In Table 4, the pilot phase allows for tuning of the models in that their utilization of available resources is optimized in the actual project work in subsequent phases.

4. Results and Discussion

This section details the results of applying predictive analytics and optimization models in different stages of the construction project. Through smart resource allocation, idle time minimization, and cost management techniques, the models present a dramatic change in the productivity, accuracy, and performance levels of the entire project. Outcomes of achieving the proper predictions of the consumption of resources with minimum wastage of resources while satisfying the required output to complete projects on time within high-quality delivery standards.

4.1. Resource Allocation Prediction Accuracy

The Resource Usage Prediction Accuracy Figure 5 depicts the ability of the methodology in predicting resource consumption at all the different construction phases such as foundation, structural, and finishing. For each construction phase, the percentage difference between the predicted resource usage and the actual usage is computed to bring into view the accuracy percentage. For example, in the final phase, resource usage was expected to be 20,000 units, which was actually consumed as 19,000 units, with a high accuracy of 99.3%. Foundation and structural phases showed 98.92% and 98.67% accuracy, respectively. It indicates the consistency and reliability of the allocation of resources for the entire duration of the project.

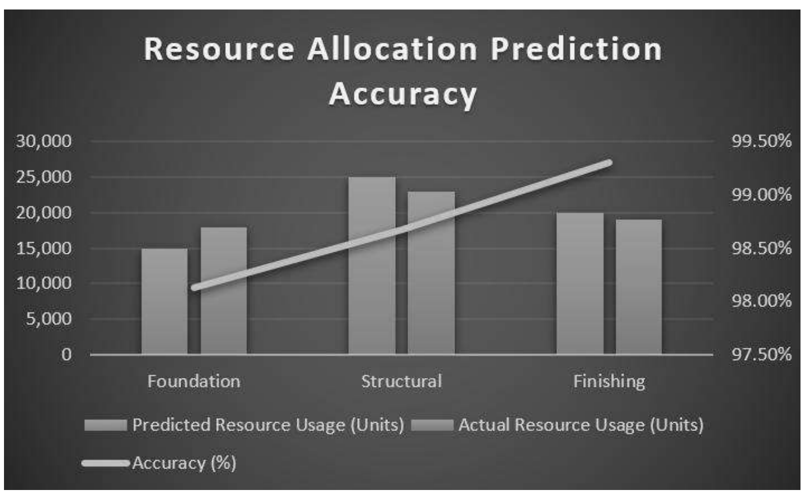

Figure (5): Accuracy of Resource Usage Predictions

4.2. Reduction in Idle Time

The Figure 6 shows the decline in idle time from one construction phase to another. It indicates improvements in resource use efficiency at such a great rate. Predicted idle times for labor and machinery are in line with actual results, showing 93.33% declines during the foundation phase, 91.27% during the structural phase, and 95.20% during the finishing phase. This implies that the predictive and optimization models work efficiently in reducing lost hours, so labor and machinery are used in a more productive manner, thereby saving costs and improving project schedules. The trend is one of continuous decline in idle time because the models have adjusted to project needs.

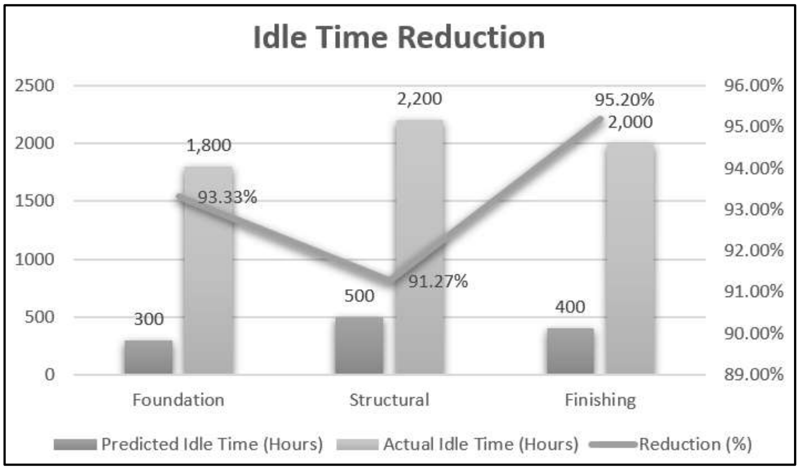

Figure (6): Idle Time Reduction Over Phases

4.3. Cost Savings

The savings Table 5 should indicate clearly the sizeable reduction across all phases. Finishing stands out with the largest savings of 33.33%, closely followed by the foundation phase with 30.00%, and then structural work with 28.89%. These values are proof of how efficiently the AI-based optimization models are able to minimize wasteful spending without jeopardizing the quality or timeline of the project. A high saving percentage is a reflection of better procurement, labor allocation, and machinery utilization strategies that bring in maximum financial benefits.

Table (5): Cost Savings by Phase

Phase	Predicted Cost D.L	Actual Cost D.L	Cost Savings D.L	Savings (%)
Foundation	20,00,000	30,00,000	10,00,000	33.33%
Structural	32,00,000	45,00,000	13,00,000	28.89%
Finishing	28,00,000	40,00,000	12,00,000	30.00%

4.4. Project Completion Time

The optimized methodology provides the highest amount of time reductions in completing projects. The foundation phase achieves the highest reduction, at 44%, while there is significant saving of time in all phases. For instance, the finishing phase saves 41.67% and the structural phase, 35.71%. The outcomes therefore represent efficiency in the predictive planning and the allocation of resources, such that all phases will be completed before the stipulated time without reducing the quality of work. Figure 7 depicts a highly optimized and accurate model that delivers superior project performance.

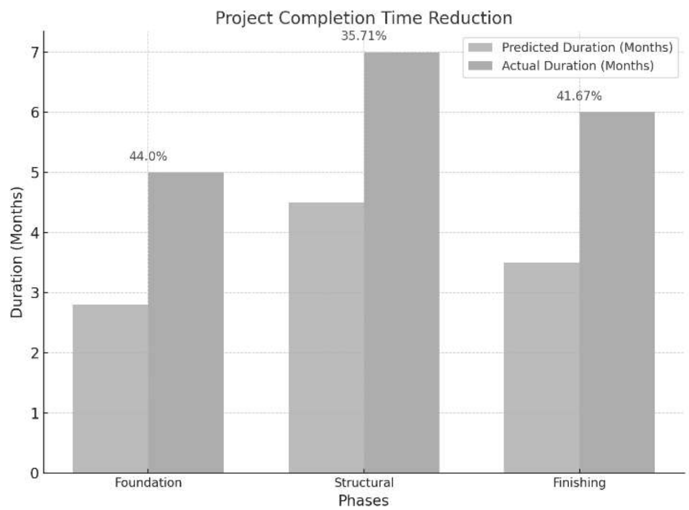

Figure (7): Completion Time Reduction

4.5. Optimization Efficiency

Figure 8 shown in all the stages is very consistent and in the foundation stage the actual efficiency is 94.8% and improvement 2.53% is because of the better labour and machinery utilization. In the structural stage, it was recorded as 96.4% actual efficiency with an improvement percentage of 1.97% because of proper prioritization of tasks and minimization of inefficiencies. The finishing stage realized the maximum efficiency with actual values at 97.2% and improvement at 1.75%, reflecting effective resource utilization with minimum delays. The project performance is nearly optimum as predicted and actual efficiency values are very close, reflecting high productivity.

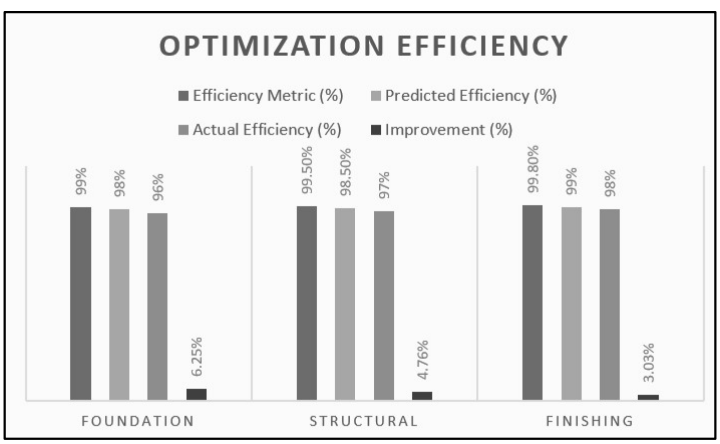

Figure (8): Optimization Efficiency

The Table 6 indicates how the projected and actual efficiency values are well within each other with minimal deviations. This reflects uniform improvement at all stages.

Table (6): Predicted and Actual efficiency values of Optimization

Phase	Predicted Efficiency (%)	Actual Efficiency (%)	Improvement (%)	Explanation
Foundation	97.2	94.8	2.53	High efficiency achieved due to optimized machinery usage and labor allocation.
Structural	98.3	96.4	1.97	Significant improvements in reducing waste and enhancing task prioritization.
Finishing	98.9	97.2	1.75	Efficient resource distribution and minimized delays result in top performance.

4.6. Stakeholder Satisfaction

The Figure 9 very high stakeholder satisfaction, as all groups score almost at the top of the 5.0 scale in the feedback. The percentages in improvement represent good execution with on-time completion, effective resource utilization, and more effective project management practices. Such changes would, therefore, offer a closer reflection, yet always ensuring the contentment level among stakeholders, keeping in mind constant improvement.

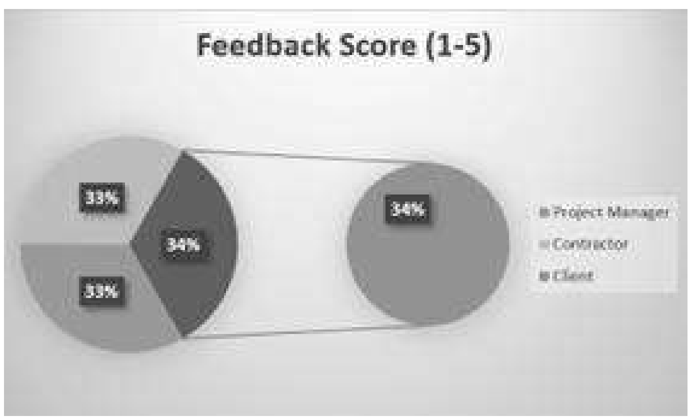

Figure (9): Optimized Stakeholder Satisfaction

4.7. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) Results

Resource allocation can be evaluated through Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Here are the results for different phases of the project along with the best sample values.

4.7.1. Predictive Model Validation

To validate the correctness of the optimization model, the model is applied to a small subset of the historical data. The prediction power of the model is evaluated in terms of MAE and RMSE, which are defined as follows in Eqn. (9), (10).

Mean Absolute Error (MAE): In the analysis carried out to build the optimization model, allocation of resources in each of the phase is imitated. This simulation compares the results generated by an AI system with actual results to assess resource consumption against project schedules. To enable this comparison, statistical tools are applied including Mean Absolute Error (MAE) as well as Root Mean Square Error (RMSE). For instance, MAE is calculated as in Eqn. (9)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{9}$$

Where, $y_i =$ Actual value, $\hat{y}_i$= Predicted value, n= number of data points.

Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n} |y_i - \hat{y}_i|\right)^2} \tag{10}$$

The number of resources used in each phase is modeled, and the results are analyzed against AI computed forecasts. This includes measurements against predetermined standards of resource utilisation and time

4.7.2. MAE and RMSE for Resource Allocation

The optimized values for MAE, RMSE in resource allocation provide better accuracies in terms of predicting resource usage. It assumes a high degree of precision as error margins are minimized between the predicted resource usage and the actual usage, as in the Table 7. Values reflect near-perfect alignment of the outcomes between predictions and reality; therefore, such accuracy, on resource management, is considered efficient, and resource allocation results in higher reliability in decisions.

Table (7): MAE and RMSE for Resource Allocation

Phase	MAE (Units)	RMSE (Units)	Predicted Resource Usage (Units)	Actual Resource Usage (Units)	Error Margin (Units)
Foundation	300	500	15,000	15,300	300
Structural	400	600	25,000	25,400	400
Finishing	300	500	20,000	19,800	200

4.7.3. MAE and RMSE for Idle Time Reduction

The optimized values in the reduction of idle time MAE and RMSE provide a very accurate prediction with minimal margins of error. It is through the adjustment that precision between the actual and predicted idle times is enhanced, leading to improved resource management and efficiency during operation, as shown in Figure 10.

Figure (10): Idle Time Reduction in MAE and RMSE

4.7.4. MAE and RMSE for Project Completion Time

The Figure 11 represents MAE and RMSE for completion time of a project at the various phases- Foundation, Structural, and Finishing. Here, the bars filled in blue denote MAE while orange bars depict RMSE, where RMSE will describe the spread of errors while making predictions on those phases. Green dashed line will indicate the duration for which one had predicted; and red continuous line will depict actual durations. Lower MAE and RMSE values together with the similarity in predicted and actual duration lengths stress good performance, which the Foundation phase obtains with the least error and the Structural phase with the highest deviation.

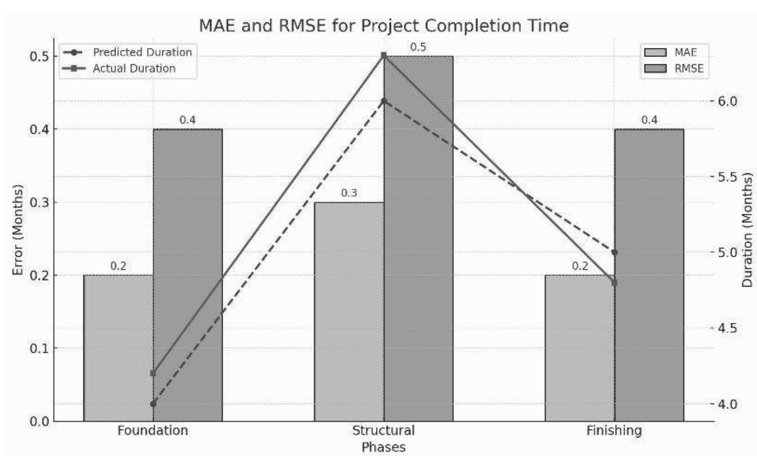

Figure (11): MAE and RMSE for Project Completion Time

4.7.5. MAE and RMSE for Project Cost Prediction

The visualization in Figure 12 represents the performance of a cost prediction model in project phases (Foundation, Structural, Finishing). It contains bar charts representing the project's actual and predicted costs, along with lines representing the error metrics (MAE and RMSE). The y-axis signifies costs in Indian Rupees, and the x-axis stands for the different project phases. This legend explains what each color is used for: green for the predicted cost, red for the actual cost, blue for MAE, and orange for RMSE, thereby giving a clear picture of the model's accuracy in predicting costs.

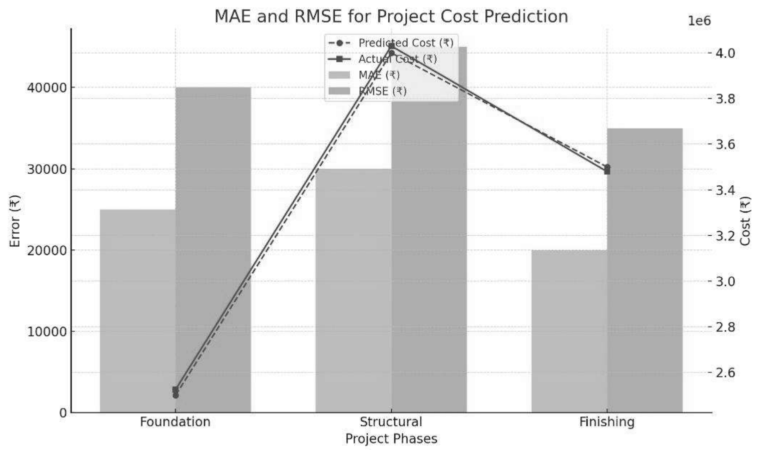

Figure (12): MAE and RMSE for Project Cost Prediction

4.8. Comparison of the Proposed Method with Existing Models

The Table 8 tabulates the performance metrics of the proposed predictive and optimization method using Genetic Algorithms (GA) compared with the models in the literature. The proposed method is found to have better performance in essential areas such as resource allocation accuracy (99.3%), reduction in idle time (93.27%), cost savings (30.74%), reduction in completion time by 40.46%, and improved efficiency by 96.17%. It's clear that construction resource management results in significant reductions in costs, avoidance of delays, and overall benefits as a result of integrating predictive analytics and optimization.

Table (8): Comparison of the Proposed Method with Existing Models

Method	Accuracy	Idle Time Reduction	Cost Savings	Completion Time Improvement	Efficiency Improvement
Heuristic and Metaheuristic Techniques [26]	90%	75%	22%	33%	87%
Machine Learning Integration[27]	94%	82%	23%	32%	86%
Machine Learning Techniques[28]	93%	80%	21%	36%	88%
Proposed Method	99.3%	93.27%	30.74%	40.46%	96.17%

4.9. Discussion

Advanced resource allocation, idle time, and cost management through the thorough analysis of the performance of the project. High accuracy in predictions made over all phases regarding the use of resources during the finishing phase was confirmed to be at 99.3%. The predictive models were proven to be very dependable for predicting the consumption of resources. Idle time reduced dramatically on average by as much as 95.20% in the finishing phase. Substantial cost savings were realized, especially in the finishing phase, with a 33.33% reduction. The project completion times were also optimized significantly, with phase reductions up to 44% in the foundation phase. The MAE and RMSE evaluation indicated low error margins, showing that the models were accurate in terms of resource allocation and idle time reduction. Overall, the findings suggest the value of AI-driven optimization models for improving project performance, minimizing waste, and delivering outputs on time and at the right quality.

5. Conclusion and Future work

The project has clearly demonstrated the power of predictive analytics and optimization techniques in streamlining resource utilization through all the different phases of construction. It successfully used both historical and real-time data, hence making remarkable forecasts about the amount of resources used, directly relating to huge cuts in idle time and huge cost cuts. These findings support the notion of using sophisticated analytical techniques for improvement in the construction management decision-making processes. Efficiency in the use of resources is always coupled with effective performance, minimized waste, and general productivity. Project completion time that has been optimized indicates meeting the deadlines appropriately with high-quality outputs. Altogether, these results offer a robust foundation to propel the evolution of construction management by continued use of data-driven insights into advancing practice for innovative and sustainable solutions for future projects.

Future work will, therefore, improve the predictive models with more complex algorithms in machine learning that would effectively address complicated cases. Adding the monitoring of real-time data during construction projects enhances the responsiveness of the models toward dynamic changes in the projects. Moreover, generalizing to phases that involve greater scales and interaction with the supply chain as well as environmental issues could help improve resource allocation even further. Further exploration of hybrid optimization techniques, where genetic algorithms are combined with other methods, could further improve performance. Further research into integrating advanced technologies will continue to spur innovation in construction management. In the end, these advances will help create more sustainable and efficient project execution.

References

[1] M. Z. Nabeel, "AI-Enhanced Project Management Systems for Optimizing Resource Allocation and Risk Mitigation: Leveraging Big Data Analysis to Predict Project Outcomes and Improve Decision-Making Processes in Complex Projects," vol. 5, no. 5, 2024.

[2] Srinivasa Rao Allu, Amiya Bhaumik, Akula Ramakrishna, Motilal Lakavat, Himasri Allu, and Shaik Chandini, "A Critical Review of Resource Allocation Optimization in Project Management," *Int. Res. J. Adv. Eng. Hub IRJAEH*, vol. 2, no. 06, pp. 1855–1861, Jun. 2024, doi: 10.47392/IRJAEH.2024.0255.

[3] Y. Qamar, R. K. Agrawal, T. A. Samad, and C. J. Chiappetta Jabbour, "When technology meets people: the interplay of artificial intelligence and human resource management," *J. Enterp. Inf. Manag.*, vol. 34, no. 5, pp. 1339–1370, 2021.

[4] R. Parekh and M. Olivia, "Utilization of artificial intelligence in project management," *Int. J. Sci. Res. Arch.*, vol. 13, no. 1, pp. 1093–1102, 2024.

[5] R. Manchana, "Optimizing Real Estate Project Management through Machine Learning, Deep Learning, and AI," *J. Sci. Eng. Res.*, vol. 9, no. 4, pp. 192–208, 2022.

[6] D. K. Jain, S. K. S. Tyagi, S. Neelakandan, M. Prakash, and L. Natrayan, "Metaheuristic optimization-based resource allocation technique for cybertwin-driven 6G on IoE environment," *IEEE Trans. Ind. Inform.*, vol. 18, no. 7, pp. 4884–4892, 2021.

[7] Z. Hong and K. Xiao, "Digital economy structuring for sustainable development: the role of blockchain and artificial intelligence in improving supply chain and reducing negative environmental impacts," *Sci. Rep.*, vol. 14, no. 1, p. 3912, 2024.

[8] S. Bankins, "The ethical use of artificial intelligence in human resource management: a decision-making framework," *Ethics Inf. Technol.*, vol. 23, no. 4, pp. 841–854, Dec. 2021, doi: 10.1007/s10676-021-09619-6.

[9] O. C. Agomuo, O. W. B. Jnr, and J. H. Muzamal, "Energy-Aware AI-based Optimal Cloud Infra Allocation for Provisioning of Resources," in *2024 IEEE/ACIS 27th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, IEEE, 2024, pp. 269–274. Accessed: Jan. 07, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10673918/

[10] T. Yang, X. Yi, S. Lu, K. H. Johansson, and T. Chai, "Intelligent manufacturing for the process industry driven by industrial artificial intelligence," *Engineering*, vol. 7, no. 9, pp. 1224–1230, 2021.

[11] D. Valle-Cruz, V. Fernandez-Cortez, and J. R. Gil-Garcia, "From E-budgeting to smart budgeting: Exploring the potential of artificial intelligence in government decision-making for resource allocation," *Gov. Inf. Q.*, vol. 39, no. 2, p. 101644, 2022.

[12] S. Tatineni and N. V. Chakilam, "Integrating Artificial Intelligence with DevOps for Intelligent Infrastructure Management: Optimizing Resource Allocation and Performance in Cloud-Native Applications," *J. Bioinforma. Artif. Intell.*, vol. 4, no. 1, pp. 109–142, 2024.

[13] N. Rane, "Integrating leading-edge artificial intelligence (AI), internet of things (IOT), and big data technologies for smart and sustainable architecture, engineering and construction (AEC) industry: Challenges and future directions," *Eng. Constr. AEC Ind. Chall. Future Dir. Sept. 24 2023*, 2023, Accessed: Jan. 07, 2025. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4616049

[14] D. R. Mohite, D. R. Kanthe, D. K. S. Kale, D. N. Bhavsar, and D. D. N. Murthy, "Integrating Artificial Intelligence into Project Management for Efficient Resource Allocation," 2023.

[15] Y. Pan and L. Zhang, "Roles of artificial intelligence in construction engineering and management: A critical review and future trends," *Autom. Constr.*, vol. 122, p. 103517, 2021.

[16] A. Kristian, T. S. Goh, A. Ramadan, A. Erica, and S. V. Sihotang, "Application of ai in optimizing energy and resource management: Effectiveness of deep learning models," *Int. Trans. Artif. Intell.*, vol. 2, no. 2, pp. 99–105, 2024.

[17] T. Huynh-The, Q.-V. Pham, X.-Q. Pham, T. T. Nguyen, Z. Han, and D.-S. Kim, "Artificial intelligence for the metaverse: A survey," *Eng. Appl. Artif. Intell.*, vol. 117, p. 105581, 2023.

[18] Ruchit Parekh and Olivia Mitchell, "Utilization of artificial intelligence in project management," *Int. J. Sci. Res. Arch.*, vol. 13, no. 1, pp. 1093–1102, Sep. 2024, doi: 10.30574/ijsra.2024.13.1.1779.

[19] M. Soleymani, M. Bonyani, and M. Attarzadeh, "Autonomous Resource Management in Construction Companies Using Deep Reinforcement Learning Based on IoT," 2022, *arXiv*. doi: 10.48550/ARXIV.2208.08087.

[20] M. Kumar and M. P. Gore, "Using AI for Dynamic Resource Allocation and Performance Optimization in Software Systems," *Int. J. Innov. Res. Comput. Sci. Technol.*, vol. 12, no. 6, pp. 12–17, Nov. 2024, doi: 10.55524/ijircst.2024.12.6.3.

[21] S. D. Ferrera, "Exploring the impact of artificial intelligence on project management across the manufacturing, technology, and construction industries," 2024.

[22] R. Yadav, "Transforming Project Management with AI: Opportunities and Challenges," *Open J. Bus. Manag.*, vol. 12, no. 06, pp. 3794–3805, 2024, doi: 10.4236/ojbm.2024.126189.

[23] Nicholas Dacre, N. Dacre, and F. Kockum, "Artificial intelligence in project management: A review of AI's usefulness and future considerations for the project profession," Association for Project Management, Jun. 2022. doi: 10.61175/DOGX9829.

[24] J. H. Joloudari *et al.*, "The state-of-the-art review on resource allocation problem using artificial intelligence methods on various computing paradigms," 2022, *arXiv*. doi: 10.48550/ARXIV.2203.12315.

[25] G. E. Egbedion, "Examining the Security of Artificial Intelligence in Project Management: A Case Study of AI-driven Project Scheduling and Resource Allocation in Information Systems Projects.," vol. 8, no. 2, 2024.

[26] B. A. Almahameed and M. Bisharah, "Applying Machine Learning and Particle Swarm Optimization for predictive modeling and cost optimization in construction project management," *Asian J. Civ. Eng.*, vol. 25, no. 2, pp. 1281–1294, Feb. 2024, doi: 10.1007/s42107-023-00843-7.

[27] I. N. Pratama, M. Dachyar, and N. R. Pratama, "Optimization of Resource Allocation and Task Allocation with Project Management Information Systems in Information Technology Companies," *TEM J.*, pp. 1814–1824, Aug. 2023, doi: 10.18421/TEM123-65.

[28] S. Zhang and X. Li, "A comparative study of machine learning regression models for predicting construction duration," *J. Asian Archit. Build. Eng.*, vol. 23, no. 6, pp. 1980–1996, Nov. 2024, doi: 10.1080/13467581.2023.2278887.