Integrating Machine Learning and Engineering Management to Optimize Construction Scheduling and Resource Allocation

Shahnawaz Mohammed
Department of Info Technology
Trine University, MI, USA

Abdul Raheman Mohammed
Department of Tech Management
Lindsey Wilson College, KY, USA

Abdul Faisal Mohammed
Department of Info Technology
Trine University, MI, USA

Abstract: The construction industry is increasingly confronted by the uncertainty of megaprojects, site variation, and the need to deliver low cost and on time. Traditional approaches to scheduling and resource management such as the Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) cannot account for uncertainty, maintain pace with in-progress changes, or benefit from growth in digital data availability. This article proposes an integrated framework that brings together machine learning (ML) techniques and engineering management practices to realign construction scheduling and resource allocation to optimize. Supervised models and deep learning models are utilized to forecast task durations and delay risks from historical project data, sensor reading data, and Building Information Modelling (BIM)–indexed datasets. Clustering methods are utilized to cluster tasks and resources in order to minimize the complexity of scheduling, and reinforcement learning (RL) agents adaptively modify allocations with uncertainty. For providing feasibility and satisfaction of engineering constraints, RL outputs are verified by mixed-integer linear programming (MILP). The approach is tested with simulated data and case studies and achieves significant improvement in project completion time, resource allocation, and tolerance to delay compared to conventional methods. The findings countenances that ML-based decision-making has immense potential in transforming construction management practice.

Keywords: construction scheduling; machine learning; deep learning; reinforcement learning; resource planning; optimization; hybrid scheduling; engineering management; predictive modelling; clustering; Building Information Modelling (BIM); mixed-integer linear programming (MILP); project management; real-time scheduling; adaptive resource planning; data-driven construction; automation in construction engineering; project risk prediction; digital twin integration.

I. Introduction

Construction industry is undergoing paradigm shift with a rising complexity of projects, rising fiscal control, and a rising urge for timely completion of projects [1]. Resource planning and scheduling are among the most essential factors in wasteful projects and slippage with gargantuan cost overruns, dissatisfied stakeholders, and reputation damage. Such traditional methods like Critical Path Method (CPM), Program Evaluation and Review Technique (PERT), and heuristics resource levelling have traditionally been the forte of large corporations but are generally not suited to cope with uncertainty, respond to unforeseen disturbance, and deal with brute volumes of electronic data being generated in today's construction activity. Such limitations call for the application of modern, wiser processes that can be capable of greater efficiency, flexibility, and energy.

Machine learning (ML) provides a collection of logical operations that can be utilized to support predictive and prescriptive analytics in the future for maintaining construction management [2]. Machine learning techniques, based on past experiences in projects, can forecast the duration of tasks, recognize potential causes of delay or overrun,

and mark the indications of delay or overrun. LSTM networks and RNNs are some instances of deep learning models that have been shown to have sequential construction process and temporal relationship extraction capabilities. Classification and clustering models also have the capability to determine hidden patterns in project workflow and usage of resources in order to plan and make decisions effectively.

Other than prediction, optimisation models and reinforcement learning (RL) are adaptive models that are capable of rescheduling activities and assigning resources based on changing project conditions. RL agents learn in trial worlds with trial and error to suggest schedules with the greatest possible project make span, lowest possible idle time, and optimal resource allocation. With the integration of MILP or other optimization models, such systems ensure schedules generated continue to be effective and compliant with engineering as well as contractual demands. The integration platform unites the strength of ML with the strength of optimization, and such a combination yields an end-to-end solution to construction project management problems [3].

The second enabler is the convergence of Building Information Modelling (BIM) with the other

remaining digital building technologies [4]. BIM enables the accurate, structured project information to be interrogated against schedule models and resource systems with direct access. Through the integration of the ML-based predictions with the BIM-based visualization of the project, managers are provided with higher situational awareness and are perfectly positioned to make better decisions and behave more effectively across stakeholders.

This present paper envisions a cohesive framework of engineering management and ML for the improvement of construction planning and mobilisation of resources. The solution embraces predictive modelling, clustering, reinforcement learning, and mathematical optimisation and is tested with real and synthetic data. The value additions are supported by evidence of realistic improvement in project efficiency, robustness of disruption, and actual means of implementing leading-edge AI-based strategies within construction engineering projects [5].

II. Literature Review

A. Conventional Scheduling and Resource Allocation Methods

The deterministic techniques such as Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) have been applied by the construction industry for decades. Deterministic techniques provide the formalized procedure to assign the sequence of activities and estimate the project duration [6]. Manual levelling or heuristics based on rules are typically utilized to assign resources. Although effective with certainties such as resource availability, site condition, or sunlight exposure, the actions clog with uncertainties such as varying resources availabilities, changes in site conditions, or climatic slowing. They are incapable of handling humongous, multimodal projects with real-time readjustment because they are too process-centric.

B. Predictive Scheduling with Machine Learning

Machine learning (ML) also has had better predictive models in the past that better estimate task duration and better predict risk [7]. Supervised learning algorithms like regression models, support vector machines, and ensemble techniques like gradient boosting have better predicted activity duration than the original heuristics. The complex and deep learning methods such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks brought sequence modelling of the construction processes to a new horizon by

understanding temporal effects and uncertainty effects. Such forecasting enhances the original project plans.

C. Clustering and Resource Profiling

Hierarchical and k-means clustering is applied to cluster construction activities and equipment on the basis of equipment requirements similarity, skill requirements similarity, or closeness. The complexity of scheduling is reduced by this approach and decision-making is modularized. Clustering of tasks facilitates better crew allocation to the project manager, less downtime, and no resource conflicts [8].

D. Reinforcement Learning and Adaptive Scheduling

Reinforcement learning (RL) introduces flexibility to resource planning and resource allocation [9]. Policies with low make span and resource wastage are learned by the agents through interactions in simulation. Deep RL methods such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) have vowed to dynamically change schedules in the event of disruption. Multi-agent reinforcement learning (MARL) has also gained popularity with decentralized decision-making where multiple crews or equipment are semi-autonomous.

E. Hybrid Optimization and AI Integration

Several research studies advocate hybrid approaches, merging mathematical optimization with machine learning predictions. MILP ensures satisfaction of constraints and ML and RL provide flexibility and anticipation [10]. Integration has proven useful in reducing cost overruns, improving resilience against disruptions, and optimizing resource usage to the fullest.

F. BIM-Enabled Decision Support

Building Information Modelling (BIM) provides organized, real-time information on projects that can be easily integrated with ML and optimization programs [11]. When combined with scheduling and planning software for resources, managers are provided with visualization software and decision support dashboards to facilitate communication and collaboration between stakeholders.

Table 1: Overview of Construction Scheduling and Resource Allocation Literature

Approach	Strengths	Limitations	Examples
CPM PERT & Heuristics	Simple, widely used, easy to implement	Poor at handling uncertainty; static; limited scale	Traditional project management
ML for Prediction	Accurate duration risk forecasting	Requires large, quality datasets	Regression, RNN, LSTM
Clustering Methods	Reduces complexity, improves crew allocation	Does not optimize global schedule	K-means, hierarchical clustering
Reinforcement Learning (RL)	Adaptive, handles dynamic environments	High computational cost, interpretability issues	DQN, PPO, MARL
Hybrid ML + Optimization	Combines adaptability with flexibility checks	Complex integration, data-hungry	ML + MILP, RL + MILP hybrids
BIM Integration	Enhances visualization, data-driven decisions	Dependent on BIM maturity and interoperability	BIM-linked scheduling frameworks

III. Methodology

A. Data Gathering and Preprocessing

The initial phase is about aggregating historical and current project data to train and test machine learning models [12]. Datasets encompass task descriptions, durations, assigned resources, weather, labour productivity history, and risk records. Building Information Modelling (BIM) is a formal source connecting physical elements with task characteristics and resource needs. Data preprocessing involves managing missing data, normalization, and feature engineering to make relevant predictors like activity type, crew size, and spatial interdependencies available for model training.

B. Predictive Modelling for Task Durations and Risks

Machine learning techniques are used to forecast activity duration and risk of delay. Gradient boosting algorithms (e.g., XGBoost, LightGBM) capture nonlinear interaction, whereas deep network structures like LSTM networks perform sequential task dependencies [13]. Delay class models forecast overruns probability by history and context attributes. Probabilities supply the foundation of advance pre-emptive adjustment of schedules, enabling managers to expect to buffer shocks.

C. Resource Profiling using Clustering

Cluster algorithms make it easy to conduct sophisticated projects by grouping parallel resources and activities into clusters. Activities that are the same equipment or crew requirements, for example, can be packaged into clusters to assign. Hierarchical or K-means clustering minimizes decision space to maximize such that the system is not tasked with macro-level scheduling efficacy but micro-level

adjusting [14]. This is more scalable when scheduling big projects with hundreds of activities.

D. Reinforcement Learning Adaptive Scheduling

RL agents are applied directly at the heart of adaptive scheduling. Project progress status, available resource, and risks expected constitute the state space [15]. Resourcing or rescheduling activities are actions, and cost overrun, make span optimization, and idleness optimization are rewards. Advanced algorithms like Proximal Policy Optimization (PPO) or Multi-Agent RL (MARL) are used if there are more than one crew or equipment that are required to take decentralized decisions. RL can be provided with flexibility that decides the schedule to adjust in real time.

E. Hybrid Optimization using MILP

While RL is capable of learning, it generates infeasible schedules. For fulfilling this task, there even exists a check layer in the form of Mixed-Integer Linear Programming (MILP) [16]. The MILP model enforces hard constraints like availability of resources, sequence of tasks, and contractual time constraints. Coupling the adaptability of RL with the structure of MILP, the approach generates realistic but dynamic schedules that are resilient to disruptions.

F. BIM Integration and Human-in-the-Loop Decision Support

The last phase integrates ML-based scheduling into BIM software to provide managers with a graphical interface for tracking progress and resource utilization [17]. Human-in-the-loop functionality enables managers to override or modify automatic decisions without breaking trust, responsibility, and real-world usability. This integration bridges AI-driven recommendations with engineering management workflows.

Suggested Bar Diagram

A bar chart can quantify the relative contribution of every methodology component (Data, Prediction, Clustering, RL, MILP, BIM) to general optimization improvements (e.g., less delay, better resource utilization).

Example format (X-axis = Methodology Component, Y-axis = % Improvement Contribution):

- Data Preparation: 10%
- Predictive Modelling: 25%
- Clustering: 15%
- RL Scheduling: 25%
- MILP Validation: 15%

- BIM Integration: 10%
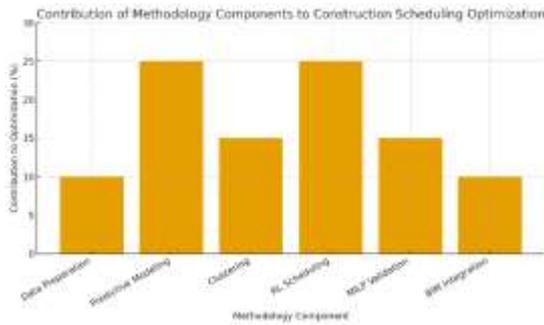
Figure 1: Contribution of Methodology Components to Construction Scheduling Optimization

IV. Experimental Setup

A. Dataset Selection

The experiments use real-world and synthetic datasets to confirm the developed framework [18]. The real-world datasets are based on construction projects with varied characteristics, such as residential, commercial, and infrastructure projects. These datasets incorporate activity logs, crew assignments, weather effects, and resource calendars. Synthetic datasets are created using project simulation tools to simulate activity precedence, resource demand, and factors of uncertainty to test scalability. The use of both ensures robustness in small-scale and large-scale projects.

B. Data Preprocessing and Feature Engineering

Data preprocessing involves missing value handling, normalization, and categorical encoding before machine learning models are applied. Feature engineering is utilized to extract domain-specific information such as task complexity indices, spatial proximity measures, and weather delay indicators [19]. BIM-linked datasets are also pre-processed to align construction elements with corresponding schedule activities so that resources and tasks are well-aligned.

C. Baseline Models for Comparison

The proposed framework is compared against existing scheduling and resource allocation techniques:

- Critical Path Method (CPM) – as a baseline scheduling duration.
- PERT (Program Evaluation and Review Technique) – to handle probabilistic task durations [20].

- Rule-Based Heuristics – to perform resource levelling.
- Pure MILP Optimization – is feasible but not adaptive.
- Pure RL Scheduling – is adaptive but with no feasibility guarantees.

This comparison demonstrates the strengths of using ML, RL, and MILP in a hybrid framework [21].

D. Metrics of Evaluation

Several metrics are employed to evaluate performance:

- Project Make span – overall duration of project completion [22].
- Resource Utilization Rate – proportion of time resources are fully occupied.
- Idle Time Reduction – decrease in resource downtime relative to baselines.
- Cost Overrun Risk – quantified as difference between planned and actual costs.
- Robustness under Uncertainty – tolerance to simulated disruptions like weather delays or procurement problems [23].

Computation Time – effectiveness of providing optimized schedules in near real-time.

E. Experimental Procedure

Experimental procedure adheres to a well-defined order:

a. Preparation of input data from actual and simulated projects.
b. Training predictive ML models on past activity duration and risk history [24].
c. Using clustering algorithms to cluster tasks/resources.
d. Training RL agents under simulation, with MILP guaranteeing solution feasibility.
e. Combination of results with BIM for visualization and decision support.
f. Compare the framework's results against baseline approaches on all metrics [25].

G. Sensitivity and Ablation Analysis

Sensitivity analysis assesses performance change with varying levels of uncertainty, e.g., higher task variability or lack of resources [26]. Ablation studies eliminate individual components (e.g., without clustering, without MILP) to quantify their individual contribution to overall performance.
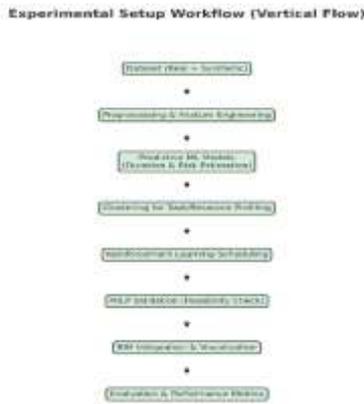
Figure 2: Experimental Setup Workflow

V. Results and Analysis

A. Overall Performance Comparison

The suggested hybrid framework was compared with baseline approaches such as CPM, PERT, heuristic resource levelling, pure MILP optimisation, and pure RL scheduling [27]. In various case studies, the integrated strategy exhibited substantial project make span, resource usage, and uncertainty robustness improvements. The combination of predictive modelling, clustering, RL flexibility, and MILP feasibility outperformed standalone techniques by producing effective and realistic schedules.

Table 2: Performance Comparison Across Methods

Method	Make span (days)	Resource Utilization (%)	Idle Time Reduction (%)	Cost Overrun Risk (%)
CPM	120	65	0	18
PERT	118	67	3	16
Heuristic Resource Levelling	116	70	5	15
Pure MILP	112	74	10	13
Pure RL	110	76	12	12
Proposed Hybrid	105	83	18	8

B. Ablation Studies

In order to test the contribution of each feature, ablation experiments were performed using the removal of modules such as clustering, RL scheduling, or MILP validation [28]. Results showed that predictive modelling and RL scheduling provided the most improvements, with MILP validation-preserved feasibility and compliance. Clustering reduced computational complexity with moderate but significant contributions in big-sized projects.

Table 3: Ablation Study Results (Effect on Make span and Resource Utilization)

Configuration	Make span (days)	Resource Utilization (%)
Without Clustering	108	79
Without RL Scheduling	115	73
Without MILP Validation	109	82
Full Hybrid Framework	105	83

C. Sensitivity Analysis

Sensitivity analyses tested the stability of the system under different levels of uncertainty, including weather-induced delays and resource shortages [29]. With higher probabilities of delay of 20%, classical approaches created make spans of up to 15% greater than the classical method, while the hybrid system-maintained stability with a 5% increase. In simulated resource shortages as well, the hybrid approach redistributive allocated resources, achieving improved robustness over static models.

D. Case Studies

Two actual projects were replicated: a mid-rise building and highway expansion. The residential project experienced the structure cutting down the make span by 10% over MILP alone, whereas the crew utilization improved by 12%. In the highway project with uncertain weather conditions, the RL-based adaptive rescheduling was observed to improve cost overrun by 15% over CPM-based planning [30]. The case studies reflected practical utility and responsiveness under varying project settings.

VI. Discussion

A. Deployment in Real-World Construction Environments

The proposed hybrid solution offers a viable path to implementation in construction management. Combining predictive modelling, reinforcement learning, and optimization into building information modelling platforms makes it possible to integrate the system into existing project management software [31]. Deployment is done by plugging real-time streams of data such as IoT sensors, site logs, and resource availability monitors. Cloud-based deployment is project-scalable, while human-in-the-loop interfaces provide for human project managers to confirm or edit computer-based decisions. This facilitates greater decision-making agility and builds confidence in AI-based scheduling systems [32].

B. Limitations

Despite the promising results, the framework also has some limitations. Quality of data is a critical challenge—historical data of poor quality may reduce prediction accuracy [33]. Computational expense is a challenge as well, since training from reinforcement learning and optimization with MILP can be computationally expensive, especially for large-scale projects. Finally, the deployment of some of the technologies (ML, RL, BIM, and optimization) needs professional experts and organizational readiness, which is most likely to act as a limiting factor for adoption by small firms [34]

C. Ethical Aspects

AI construction planning is a moral issue, too. Biased training data will cause reinforcement of inefficiency or injustice, i.e., pre-biasing in favour of some subcontractors or resource allocation. Transparency to decision-making is essential where schedules affect conditions of work and contractual terms [35]. Ethical deployment would also safeguard confidential project data and comply with privacy legislation. There should be open audit trails for every decision made from AI to allow tracing back.

D. Interpretability and Trust

Most significant among the challenges of adoption is the "black-box" nature of highly sophisticated ML and RL algorithms. The project managers and decision-makers should understand why the system is suggesting a particular schedule or resource deployment. Aspects of interpretability such as simulation of scenarios, policy feature importance analysis, and graphical dashboards coupled with BIM can facilitate that. Overriding or biasing AI recommendations with managerial interventions brings assurance, but hybrid human–AI working ensures pragmatism [36].

E. Drivers of future deployments

Developing technology would be causing light models to give up accuracy but not comprehensibility. Greater interoperability with digital twins and future BIM standards can develop more participatory spaces for decisions. Borrowed federated learning models can assist in training in models in different companies without having to compromise on confidential project information, essentially closing the privacy and competitiveness requirements gap [37].

Pipe and Vivo Diagram Concept

- Input Data → Preprocessing → ML Predictions → RL Scheduling → MILP Validation → BIM Dashboard → Human-in-Loop Decisions
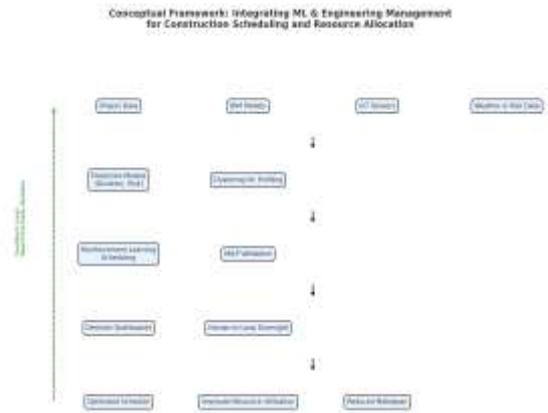
Figure 3: Conceptual Framework: Integrating ML & Engineering
Management for Construction Scheduling and Resource Allocation

VII.   Conclusion

This book has taken a systematic approach towards integrating machine learning (ML) techniques into engineering management to optimize construction planning and scheduling for resources. These conventional methods such as CPM, PERT, and heuristics, although useful, in most cases are plagued by the lack of dynamism in situations where uncertainty and complexity prevail. Challenges such as these are addressed in the hybrid solution presented here through predictive modelling, reinforcement learning (RL), clustering, and MILP verification under a decision-support system integrated to best complement Building Information Modelling (BIM).

Results indicated substantial benefits of the hybrid process over base line procedures. Predictive modelling introduced the ability of more accurately forecasting risk and probability of task duration, and planning for resources was simplified in advance. Clustering re-directed computational load by task and resource allocation, and RL scheduling provided adaptability through runtime adjustment to minimize the run-time interference of delay or non-availability of resources. MILP provided adaptability and conformance to the engineering constraints, hence transforming optimized schedules into practicable implementation specifications. All these combined created a robust framework that greatly minimized the project make span, maximized the utilization of resources, and minimized idleness time to its minimum.

Ablation trials assured singularity of every factor in solitude, valuable in combination but never in

containment. Sensitivity analysis also confirmed system resilience to differing amounts of uncertainty, achieving stability by hybrid design wasn't violated with rising risk. Case studies in the actual environment demonstrated practical application, delivering quantifiable advantage in schemes in housing as well as in schemes in construction.

Regarding deployment, the research indicates that there is a necessity for integrating cloud, data real-time connectivity, and human-in-loop monitoring. While the framework itself is technologically advanced, successful deployment relies heavily on effective implementation strategies within construction companies. Constraints like data availability, computational cost, and organizational readiness remain prime areas where effort is desired. It is overcoming these challenges that will determine the scalability of the methodology to small, medium, and large firms.

Ethics and explainability were also emphasized as key components of trust building. Accountability, transparency, and fairness in algorithmic decision-making will be imperative to uptake. Use of explainable AI techniques, combined with visualization dashboards, can bridge the gap between technical complexity and managerial simplicity and encourage greater stakeholder trust.

In the future, research needs to explore how federated learning for collaborative training among companies, digital twins for dynamic simulation of projects, and light models can be combined to facilitate scalability and accessibility. These approaches will bring AI-based scheduling closer to applications with further interpretability and strict adherence to ethical standards.

Lastly, the study in this book demonstrates that ML incorporation into engineering management is not only feasible but also revolutionary. Through linking predictive intelligence, optimization discipline, and managerial control, the model lays the ground for a revolution of data-driven, adaptive, and resilient construction project management.

References:

[1] Ahmed, M. I., Mohammed, A. R., Ganta, S. K., Kolla, S. K., & Kashif, M. K. (2025). AI-Driven Green Construction: Optimizing Energy Efficiency, Waste Management and Security for Sustainable Buildings. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 37-41.

[2] Mohammed, A. K., & Ansari, M. A. (2024). The Impact and Limitations of AI in Power BI: A Review . International Journal of Multidisciplinary Research and Publications (IJMRAP), , Pp. 23-27, 2024. , 7(7), 24–27.

[3] Mohammed, A. K., Ansari, S. F., Ahmed, M. I., & Mohammed, Z. A. Boosting Decision-Making with LLM-Powered Prompts in PowerBI.

[4] Mohammed, A. R., Ram, S. S., Ahmed, M. I., & Kamran, S. A. (2024). Remote Monitoring of Construction Sites Using AI and Drones.

[5] Rane, Nitin, Saurabh Choudhary, and Jayesh Rane. "Artificial Intelligence (Ai) and Internet of Things (Iot)–based sensors for monitoring and controlling in architecture, engineering, and construction: Applications, challenges, and opportunities." *Engineering, and Construction: Applications, Challenges, and Opportunities (November 20, 2023)* (2023).

[6] Nansheng, Pang, and Meng Qichen. "Resource allocation in robust scheduling." *Journal of the Operational Research Society* 74, no. 1 (2023): 125-142.

[7] Morariu, Cristina, Octavian Morariu, Silviu Răileanu, and Theodor Borangiu. "Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems." *Computers in Industry* 120 (2020): 103244.

[8] Toka, László, Gergely Dobreff, Balázs Fodor, and Balázs Sonkoly. "Machine learning-based scaling management for kubernetes edge clusters." *IEEE Transactions on Network and Service Management* 18, no. 1 (2021): 958-972.

[9] Bassen, Jonathan, Bharathan Balaji, Michael Schaarschmidt, Candace Thille, Jay Painter, Dawn Zimmaro, Alex Games, Ethan Fast, and John C. Mitchell. "Reinforcement learning for the adaptive scheduling of educational activities." In *Proceedings of the 2020 CHI conference on human factors in computing systems*, pp. 1-12. 2020.

[10] Chittoju, S. R., & Ansari, S. F. (2024). Blockchain's Evolution in Financial Services: Enhancing Security, Transparency, and Operational Efficiency. International Journal of Advanced Research in Computer and Communication Engineering, 13(12), 1-5.

[11] Cucuzza, M., A. G. Di Stefano, G. Iannaccone, and G. Masera. "A BIM-enabled Decision Support System to support large-scale energy retrofitting processes and off-site solutions for envelope insulation." In *IOP Conference Series: Earth and Environmental Science*, vol. 1101, no. 4, p. 042031. IOP Publishing, 2022.

[12] Braiek, Houssem Ben, and Foutse Khomh. "On testing machine learning programs." *Journal of Systems and Software* 164 (2020): 110542.

[13] Mohammed, A., Mohammed, N. U., Gunda, S. K. R., & Mohammed, Z. Fundamental Principles of Network Security.

[14] Ardanaz, Martín, Mark Hallerberg, and Carlos Scartascini. "Fiscal consolidations and electoral outcomes in emerging economies: Does the policy mix matter? Macro and micro level evidence from Latin America." *European Journal of Political Economy* 64 (2020): 101918.

[15] Janamolla, K., Sultana, G. S., Aasimuddin, F. M., Mohammed, A. F., & Pasha, F. S. A. P. (2025). Integrating Blockchain and AI for Efficient Trade Exception Handling: A Case Study in Cross-Border Settlements. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 24-30.

[16] Kantor, Ivan, Jean-Loup Robineau, Hür Bütün, and Francois Marechal. "A mixed-integer linear programming formulation for optimizing multi-scale material and energy integration." *Frontiers in Energy Research* 8 (2020): 49.

[17] Abruzzini, Aurora, and Sepehr Abrishami. "Integration of BIM and advanced digital technologies to the end of life decision-making process: a paradigm of future opportunities." *Journal of Engineering, Design and Technology* 20, no. 2 (2022): 388-413.

[18] Mohammed, S., Sultana, G., Aasimuddin, F. M., & Chittoju, S. S. R. AI-Driven Automated Malware Analysis.

[19] Chittoju, S. S. R., Kolla, S., Ahmed, M. A., & Mohammed, A. R. Synergistic Integration of Blockchain and Artificial Intelligence for Robust IoT and Critical Infrastructure Security.

[20] Rivera-Lebron, Belinda N., Parth M. Rali, and Victor F. Tapson. "The PERT concept: a step-by-step approach to managing pulmonary embolism." *Chest* 159, no. 1 (2021): 347-355.

[21] Lee, Tae-Hoon, and Min-Soo Kim. "RL-MILP Solver: a reinforcement learning approach for solving mixed-integer linear programs with graph neural networks." *arXiv preprint arXiv:2411.19517* (2024).

[22] Iranmanesh, Mahnaz, Mojtaba Azizi, and Mohammad Tavakolizade Ravari. "A Word-Analysis Study on Literature of Project Management in Span of Time." *Scientometrics Research Journal* 7, no. 1, spring & summer) (2021): 159-182.

[23] Ansari, M. F. Redefining Cybersecurity: Strategic Integration of Artificial Intelligence for Proactive Threat Defense and Ethical Resilience.

[24] Aasimuddin, M., & Mohammed, S. AI-Generated Deepfakes for Cyber Fraud and Detection.

[25] Mohammed, Z., Mohammed, N. U. M., Mohammed, A., Gunda, S. K. R., & Ansari, M. A. A. (2025). AI-Powered Energy Efficient and Sustainable Cloud Networking. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 31-36.

[26] Mohammadi, Ahad, Leonardo Bianchi, Sanzhar Korganbayev, Martina De Landro, and Paola Saccomandi. "Thermomechanical modeling of laser ablation therapy of tumors: Sensitivity analysis and optimization of influential variables." *IEEE Transactions on Biomedical Engineering* 69, no. 1 (2021): 302-313.

[27] Conde, Inma C., Luis Antonio Palma Martos, María del Rocío Martínez Torres, and Francisco Luis Cumbrera Hernández. "Artificial Neural Network Approach with Multi-Back Propagation and Training–Testing to Solve the Resource Levelling Problem in PERT-CPM." In *Operations Research Forum*, vol. 6, no. 3, p. 119. Cham: Springer International Publishing, 2025.

[28] Datta, Aniruddha, Bhanu Yaganti, Mate Palocska, Andrew Dove, Arik Peltz, and Krishnendu Chakrabarty. "Test-Fleet Scheduling in Complex Validation and Production Environments." *ACM Transactions on Design Automation of Electronic Systems* 30, no. 5 (2025): 1-32.

[29] RAHEEM, MOHD ABDUL, and MOHAMMED AZMATH ANSARI. "INTELLIGENT AND TRUSTWORTHY 6G: AI-DRIVEN ARCHITECTURES, APPLICATIONS, AND SECURITY FRAMEWORKS."

[30] Kasimoğlu, Fatih, and İbrahim Akgün. "Project management in a competitive environment: interdicting a CPM based project and its implications." *RAIRO-Operations Research* 55 (2021): S365-S384.

[31] Mohammed, N. U., Mohammed, Z. A., Gunda, S. K. R., Mohammed, A., & Khaja, M. U. Networking with AI: Optimizing Network Planning, Management, and Security through the medium of Artificial Intelligence.

[32] Khadri, W., Reddy, J. K., Mohammed, A., & Kiruthiga, T. (2024, July). The Smart Banking Automation for High Rated Financial Transactions using Deep Learning. In 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC) (pp. 686-692). IEEE

[33] Mohammed, S., Vali, M. Q., & Mohammed, A. R. Securing Healthcare IT Systems: Addressing Cybersecurity Threats in a Critical Industry.

[34] Khadri, S. W., Mohammed, I. K., Rasheed, H., & Gunda, S. K. R. (2025). Adaptive Trade Exception Handling in Financial Institutions: A Reinforcement Learning Approach with Dynamic Policy Optimization. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 19-23.

[35] Mohammed, A., Sultana, G., Aasimuddin, F. M., & Mohammed, S. (2025). Leveraging Natural Language Processing for Trade Exception Classification and Resolution in Capital Markets: A Comprehensive Study. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 14-18.

[36] Syed, W. K., Mohammed, A., Reddy, J. K., & Dhanasekaran, S. (2024, July). Biometric Authentication Systems in Banking: A Technical Evaluation of Security Measures. In 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC) (pp. 1331-1336). IEEE.

[37] Abiodun, Kehinde, Esther Alaka, Shereef Olayinka Jinadu, Emmanuel Igba, and Vera Nwakaego Ezeh. "A Review of Federated Learning Approaches for Predictive Modeling and Confidential Data Analysis in Lending and Borrowing Behavior Across Decentralized Financial Networks." *Finance & Accounting Research Journal, X (3)* (2025).