

AI-Driven Climate-Resilient Construction Scheduling and Resource Planning (AI-CRSP)

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Abstract- The paper explored the challenges of construction scheduling that occurred due to the changes, labour availability, and productivity. This paper also explored the problems faced during construction work due to environmental factors such as extreme heat, heavy rain, and strong winds. These effects on the working conditions also slow down productivity, disturb safety plans, labour arrangements, and equipment use. During the study, it was found that traditional methods mostly take more time to handle delays in the work. These conventional methods are not suitable for the dynamic nature of the weather. The changes in the climate make the work harder during the construction period, and the frequency and intensity of disruptions also increase. In the present work, a solution is provided for addressing the problems that is based on AI Framework. This framework will maintain climate sensitivity, risks, and provide the solutions to minimize costs and emissions.

Keywords— Artificial Intelligence (AI), Resource Planning, Climate Changes, Construction Scheduling.

I. INTRODUCTION

The field of construction industry is tough. Complex and unpredictable projects are handled in this field. It includes site design, planning, and meeting regulatory requirements [1]. The construction industry is also affected by internal and external matters like other industries. The external factors include the dynamic climate and the movement of labour. Due to such problems, the projects were not delivered on time. Delays in construction scheduling are also a kind of such problem [2]. According to analysis, there are more than 45% projects that were delivered late due to adverse conditions of the weather conditions, that make the overbudget of the projects [2]. All such problems directly decrease the work flexibility and productivity, and it makes project delays and sometimes even legal problems for stakeholders [2], [3].

This paper explored the challenges and risks that are faced by the construction industry, and it also identified the reasons why there is low performance of this industry, rather than other industries like the economic industry [4]. In the study, it is analyzed that there is an 85% deficiency, which leads to delays in large projects due to limited flexible computing resources and slow response systems. These points motivate addressing these problems and the need for advanced scheduling techniques [5]. In the study, it found that there is a requirement of transformation to advanced, robust scheduling methods that can be suitable for the dynamic climate conditions and labour challenges [6]. Existing management methods are based on the small projects, fixed scheduling and past data that are not suitable for the current complex and uncertain problems [7]. The present work provide a AI-based analytical model to address such problems and to increase productivity. This model will give

resilience against environment-related disruptions [6], and will make the process more efficient by minimizing the human mistakes and the need for manual work [8].

A. Problem statement

The origin of the main problem comes from the delays of construction projects that rely on intricate planning and strong buffer management to manage the various uncertainties in the construction field [9]. The most common uncertainties are changes in schedule, which affect the entire project duration, and there is a requirement of robust risk management approach during the planning and scheduling phases [10].

Large-scale projects face serious setbacks, with approximately 80% suffering budget overruns and about 20% facing delays in schedule. Due to this, projects fail to complete on time, which is a very critical problem in projects [11]. These recurring challenges point to the requirement of finding solutions to minimize financial losses and improve project outcomes. Therefore, this paper is presented to provide a solution for it by designing and implementing effective project planning and comprehensive buffer management strategies that can confirm resilience, reduce risks, and enhance project outcome [12], [13]. The changing nature of the climate, labour shortages, and a lack of skills add another layer of complexity to construction projects, where traditional scheduling methods often fail.

Most construction schedules and resource plans have three key limitations:

- Weather is treated as a fixed buffer, not a changing risk.
- Resource plans are not aligned with climate disruptions.
- Planning is not truly adaptive.

Because of these gaps, projects become vulnerable to delays, cost overruns, safety incidents, and indirect carbon emissions (idle equipment, longer site overhead days), particularly as climate extremes become more common.

B. Motivational Example

Climate and weather are among the rapidly growing obstacles in construction planning that reduce work productivity and lead to wasted resources, especially during periods of extreme heat, rain, or wind. Below are practical examples showing why a climate-resilient schedule must actively reshape sequencing and resource planning, rather than just adding buffer time.

Rain can stop earthwork, compaction, excavation, waterproofing, painting, and concrete placement/finishing.

Saturated soils reduce equipment mobility and can trigger slope instability and dewatering needs. generic “rain allowance” does not tell you *which* tasks to avoid, *when* to shift crews, or *how* to prevent idle cranes, pumps, and labour.

In this context, climate-aware scheduling changes,

- Pull forward prefabrication, indoor MEP rough-ins, or staging tasks during forecast rain windows.
- Sequence earthwork/compaction around expected wet periods to reduce rework and failed compaction tests.
- Re-time deliveries and storage plans to avoid material damage and site access bottlenecks.

AI is useful here because it translates predictions into probabilities of disruption, quickly tests multiple potential sequencing/resource options, and suggests the best next steps. They minimize delays and downtime without causing any disruptions.

C. Objective

The focus of this work is to design and evaluate an AI-driven climate-resilient construction scheduling and resource planning approach that:

- Estimates climate-related disruption risk over the near future (e.g., next 1–14 days) using probabilistic hazard signals.
- Links climate risk to specific construction activities and trades by learning or setting sensitivity rules
- Adapts the schedule and crew allocations dynamically.

D. Contribution of the paper

This work makes four main contributions:

- A climate-aware scheduling formulation (climate + resources + constraints).
- A practical AI framework (AI-CRSP) that combines prediction and decision-making.
- A closed-loop planning and execution approach.
- A results-driven evaluation using climate-stressed scenarios.

II. RELATED WORK

This section focuses on AI applications, climate resilience, scheduling, and optimizing resource planning within the construction domain.

A. AI-based Construction Management

To handle the inherent and external complexities involved in construction projects and to ensure coordination among stakeholders, we need advanced solutions [14]. AI-based applications simplify project workflows and enhance the decision-making process due to their ability to predict, optimize, and automate. This is achieved by analyzing the datasets that were available [15]. The major changes will appear in the construction field due to their capabilities that will give significant contributions from the start of the project to completion means from the planning of the project to the implementation of the project [16], [17]. For the purpose of the example, during the analysis of 4D and 5D building modeling, Tools that are AI-activated are used for the purpose of resource management improvement, reducing waste, enhancing scheduling, and providing more efficient cost estimation [18]. These AI-based tools are used for better

and more accurate planning of projects. Due to this, overall project efficiency increases, and chances of human error are reduced [16], [19].

B. Climate Resilient Construction Practices

The practices are demonstrated to minimize the high financial costs and social disruptions due to climate-related delays and damages, because half of the construction projects are affected all over the world [21]. In the analysis, it is found that AI-based advanced computational tools are required for creating adaptive approaches that can manage environmental uncertainties and also provide support for sustainable building methods [22].

It is the requirement to include an AI model for the prediction of how the environment affects materials and structures, improving designs to make them more resilient, and managing real-time dynamic environmental conditions [23].

C. Scheduling and Resource Planning Methodologies

Precise, effective scheduling and robust resource planning are base for the delivery of projects on time in the construction field. For this purpose, various methods are used, such as the critical path method, which allows the project assessment and review of the schedule [24]. Even though such conventional ways are not suitable for handling the dynamic climate. So, there is a requirement for more adaptive and data-driven techniques [25]. There are various Tools that are AI-based, which provide a standard framework for optimization of project timelines and resource allocation. It is pointed out that such techniques have improved the capability of future prediction regarding climate-change. Due to this, there are more chances of completing projects within the specified time [25], [27].

Even though there are various approaches that are based on AI-based technologies for progress in the construction filed, climate resilience, and project scheduling. But still, there are several critical research gaps that exist. This specifically includes the quantitative analysis of AI in construction and the challenges of interoperability in BIM platforms [19]. Despite the significant advancements in AI, a comprehensive understanding of the ethical effects and governance frameworks in construction is still remains, especially data privacy and algorithmic fairness [27]. Furthermore, there is a limited focus on building sustainability within AI applications, and research on the environmental performance of construction materials is also underdeveloped, despite their significant impact on project outcomes.

III. PROPOSED METHODOLOGY

This section deals with the proposed system framework (AI-CRSP), illustrated in Fig.1. AI-CRSP is a hybrid architecture intended to be implementable with common construction data pipelines. It consists of different key stages that work together to perform the operations.

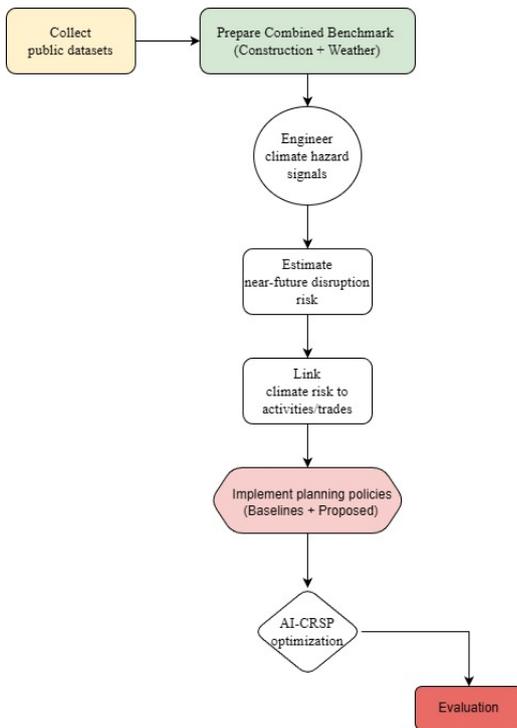


Fig. 1 Proposed methodological framework

These steps are briefly describe below.

Step 1: Collect public datasets

In step 1, we access two publicly available datasets from Kaggle: the Construction Project Resource Dataset and the World Weather Repository (Daily Updating). These datasets provide the project-side variables (resources, durations, planning attributes) and the weather-side variables (temperature, precipitation, wind, etc.) respectively. We also record dataset versions/date-of-access to ensure reproducibility, especially because the weather dataset is updated frequently.

Step 2: Create the combined benchmark dataset (Construction + Weather)

In this step, we integrate both datasets into a single benchmark table. We standardize time fields at a daily level and map each construction record (project or activity group) to a representative city from the weather dataset, then join using Date \times Location keys. The output is a merged dataset that contains construction resource fields alongside aligned daily weather indicators.

Step 3: Engineer climate hazard signals

This step converts weather-related raw data into operational risks that affect and impact construction work. It also normalizes the single hazard index, which is on a 0-1 scale. This hazard information then forms the basis for learning and planning decisions.

Step 4: Estimate near-future disruption risk

This step build a probabilistic forecasting model and estimate disruption risk. Instead of only predicting a single value, the model outputs probabilities (e.g., $P(\text{disruption})$) or quantiles of H_{t+k} , capturing uncertainty. Forecast performance is validated using probability-quality metrics such as Brier Score and calibration error (ECE).

Step 5: Link climate risk to activities/trades

In this step, climate hazards are linked to construction activities, and each activity is assigned a trade category. Furthermore, it estimates the vulnerability to potential risks. In this way, it predicts the expected output by anticipating the hazards.

Step 6: Implement planning policies (Baselines + Proposed)

In this step, we implement four comparable planning policies for benchmarking. CPM/Static ignores weather, Buffer inflates durations by a fixed percentage, Robust uses conservative (e.g., quantile-based) durations for sensitive trades, and AI-CRSP uses probabilistic hazards plus sensitivity modeling to support adaptive decisions.

Step 7: AI-CRSP rolling optimization and dynamic dispatch

In this step, AI-CRSP operates in a rolling-horizon manner: a periodic re-optimization (e.g., weekly) updates the plan using forecast risk, while daily dispatch reallocates crews among eligible tasks based on predicted productivity and safety feasibility. The method respects precedence and resource constraints while actively resequencing work to avoid high-risk hazard windows. This is the core mechanism that enables climate-resilient scheduling in execution.

Step 8: Performance evaluation

In this step, we evaluate all four policies on consistent metrics that reflect schedule and resource resilience. Key outputs include mean and P90 makespan, total cost proxy, idle crew/equipment time, and disruption exposure (how often work is scheduled during high-risk days).

IV. EXPERIMENTAL SETUP

A. Dataset Used

In this section, we have accessed two datasets from Kaggle repository. These two datasets are combined for the experiments.

(a) Construction Project Resource Dataset

This dataset is intended to represent construction project resource management at a structured, tabular level. According to the dataset description, it contains key planning inputs such as labor requirements, equipment usage, material quantities, and project durations, along with risk-related fields used to reflect uncertainty or constraints in resource allocation decisions. It provides the “project side” variables needed for AI-driven scheduling and resource planning i.e., the parameters that determine how sensitive a schedule is to disruptions and how costly resource idling can be when work is interrupted.

(b) Global Weather Repository Dataset

This dataset holds daily weather information about capital cities worldwide and describes as being updated daily. It includes 40+ weather-related features, explicitly including variables such as temperature, wind, pressure, precipitation, humidity, visibility, and air-quality-related measurements. It provides the “climate/weather side” needed to build daily hazard signals (heat, heavy rain, wind) and short-horizon disruption indicators that can drive climate-aware resequencing and resource dispatch decisions.

B. Baseline Models

Our proposed model (AI-CRSP) is evaluated across the following baseline models.

(a) Critical Path Method with Static Execution (CPM/Static) planning policy

In the CPM/Static execution, the project schedule is fixed once as a baseline, and the sequence and start times are not adjusted for weather/climate during execution. In this policy, weather/climate impacts are not explicitly considered but performance is “according to plan”.

The priority network of activities follows the form-

$$G=(A, E),$$

Each activity $i \in A$ has a nominal duration d_i . CPM calculates the earliest start/finish time using the forward-pass method:

$$ES_i = \max_{(j \rightarrow i) \in E} EF_j \tag{5}$$

$$EF_i = \max_{(j \rightarrow i) \in E} ES_j + d_i \tag{6}$$

(b) Buffer approach

In this approach, the duration of each activity (or selected activities) is inflated by a fixed percentage to handle weather uncertainty, i.e., contingency days are added, but the sequence and crew allocation remain largely static. This means that the planner attempts to absorb delays by adding “extra time”, without dynamic resequencing or daily crew re-dispatch.

If the nominal duration is d_i , then the buffer-added duration is:

$$d_i^{buff} = d_i(1 + \rho) \tag{3}$$

where ρ is the fixed buffer rate (e.g., 0.10 for 10%).

The buffer approach does not model weather as an explicit forecast or a time-varying hazard H_i . It simply covers the “average expected disruption” through a constant cushion. Therefore, it has simplicity, but in high-variability climates, it can be either under-protective (buffer less) or over-conservative (buffer more), and the issue of resource idling is not fully resolved.

(c) Robust policy

It employs more conservative planning for weather-sensitive trades/activities such as quantile-based effective durations (e.g., P80/P90) or higher safety margins so that plans remain viable even in worst-case disruptions, though this approach can often be over-conservative.

The goal is to make the schedule feasible and stable even under climate/weather uncertainty, but without frequent dynamic replanning.

If the effective duration of activity i is random/uncertain due to the weather hazard H , then robust planning can set the duration to a conservative quantile:

$$d_i^{rob} = Q_q d_i^{eff} \tag{4}$$

where $Q_q(\cdot)$ is the q -th quantile (for example, $q=0.8$ or 0.9).

Robust policies absorb uncertainty at the “planning stage” (less re-planning), but their downside is that they can be over-conservative—increasing project duration and overhead—and missing the benefit of opportunistic resequencing/crew dispatch in real-time hazard windows.

C. Evaluation Metrics

(a) Mean Makespan (Average project completion time)

Mean completion time is the average total project completion time across multiple runs/scenarios (different weather sequences or Monte Carlo simulations). In our case, it indicates how many days a project normally takes to complete with a policy (CPM/Buffer/Robust/AI-CRSP). Lower mean completion time indicates overall faster completion.

(b) P90 Makespan (90th percentile completion time / tail risk)

It is the completion time within which a project is completed in 90% of cases (only 10% of worst-case scenarios are delayed longer than this). In our case, P90 captures the “delay tail risk”—that is, how late the project could be under extreme weather/disruption. Lower P90 indicates more reliable schedule and lower worst-case delay risk.

(c) MAE (Mean Absolute Error)

It is the average magnitude of the prediction error.

$$MAE = \frac{1}{N} \sum_{n=1}^N |y_n - \hat{y}_n| \tag{7}$$

In our case, y and \hat{y} our case, these could typically be hazard indexes (H_t), disruption probability, or productivity factor (weather-adjusted output). MAE reduction means how close the model is to the average (errors in absolute value).

(d) RMSE (Root Mean Squared Error)

It is computed as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2} \tag{8}$$

In our case, RMSE is also used for hazard/productivity predictions, but it penalizes large errors more. Lower RMSE indicates lower especially “bad misses” (e.g., missing heavy rain/wind days), which is critical for scheduling.

(e) MAPE (Mean Absolute Percentage Error)

The MAPE indicates percentage-based error measure.

$$MAPE = \frac{100}{N} \sum_{n=1}^N \left| \frac{y_n - \hat{y}_n}{y_n} \right|$$

(9)

In our case it is natural to use MAPE in productivity factor, adjustment duration, or demand/resource forecasting because it tells what the average error of the model is in percent terms. Lower the MAPE means predictions are accurate in relative scale.

V. RESULTS AND DISCUSSION

A. Overall Performance of Models

Table I demonstrates CPM/Static performs worst, containing extremely low on-time rate (0.06), very high errors (MAE 47.30, RMSE 58.54), and strong negative bias (-45.74 days), meaning it systematically underestimates duration. Robust achieves the highest on-time rate (0.84) but has large positive bias (+36.37 days), indicating over-conservative predictions with still-high MAE/RMSE. Buffer substantially reduces errors (MAE 24.61, RMSE 33.16) and improves within-10% accuracy (0.73), though it remains slightly under-biased (-8.83). AI-CRSP is the most balanced containing best within-10% accuracy (0.75), lowest MAE/RMSE (23.57/31.77), and near-zero bias (~0.03), indicating accurate and well-calibrated predictions.

TABLE I. PERFORMANCE COMPARISON OF BASELINE MODELS AND PROPOSED (AI-CRSP) FRAMEWORK

Model	Accuracy On Time Rate	Accuracy Within 10pct	MAE Days	RMSE Days	MAPE	Bias Pred - Actual Days
CPM/Static	0.06	0.32	47.30	58.54	0.13	-45.74
Robust	0.84	0.39	44.85	51.54	0.18	36.37
Buffer	0.38	0.73	24.61	33.16	0.07	-8.83
Proposed (AI-CRSP)	0.50	0.75	23.57	31.77	0.07	0.025

B. Overall climate-related disruption risk

The Table II indicates CPM/Static faces the highest climate disruption exposure, with very high probabilities of any/moderate/severe disruption (0.93/0.85/0.70) and large expected disruption days (46.5), with extreme tail risk (CVaR95 = 137.14 days). Robust minimizes disruption risk the most (Any = 0.15; Severe = 0.03) and keeps expected and tail disruption days very low, but this typically reflects conservative planning assumptions. Buffer reduces risk compared to CPM but still shows meaningful disruption likelihood and tail exposure (P95 = 64.16; CVaR95 = 84.09). AI-CRSP improves over Buffer by lowering disruption probabilities and expected disruption days (11.7) and reducing tail risk (CVaR95 = 71.8), demonstrating better climate-resilient adaptation without being as conservative as Robust.

TABLE II. OVERALL CLIMATE-RELATED DISRUPTION RISK

Model	Any Disruption	Moderate Disruption	Severe Disruption	E[Disruption] n days	E[disruption] n % of plan	P90 Disruption	P95 Disruption Days	CVaR95 Disruption Days
CPM/Static	0.93	0.85	0.70	46.5	0.15	96.02	114.8	137.14
Robust	0.15	0.08	0.03	4.28	0.01	14.12	32.9	55.25
Buffer	0.61	0.42	0.24	16.7	0.05	48.46	64.16	84.09
Proposed (AI-CRSP)	0.49	0.3	0.15	11.7	0.03	37.9	52.68	71.8

CPM/Static	0.93	0.85	0.70	46.5	0.15	96.02	114.8	137.14
Robust	0.15	0.08	0.03	4.28	0.01	14.12	32.9	55.25
Buffer	0.61	0.42	0.24	16.7	0.05	48.46	64.16	84.09
Proposed (AI-CRSP)	0.49	0.3	0.15	11.7	0.03	37.9	52.68	71.8

C. Model-wise Weather Risk Exposure

Across all models, Avg and P90 Weather Risk remain identical (0.5) and the share of high-risk days (≥ 0.75) is 0.0, indicating the underlying weather-risk distribution used in this setup does not vary by policy. The key difference between these models is choices of scheduling that turns risk into exposure over time. The values of Avg Predicted Day and Avg Risk Days show this significant point. It is also noticeable that the Robust and Buffer methods tend to push work defer, which results in more accumulated risk days rather than CPM. During the analysis, it is found that Buffer stands out because of the long Duration Weighted Risk (16.7) in comparison to the other models (0.5). It shows that there is a calculation inconsistency that needs to be checked, or there is a different scaling or definition that was used.

TABLE III. MODEL-WISE WEATHER RISK PERFORMANCE

Model	Avg Weather Risk	p90 Weather Risk	Share high risk (≥ 0.75)	Duration Weighted Risk	Avg Predicted Day	Avg Risk Days
CPM/Static	0.5	0.5	0.0	0.5	295.27	147.63
Robust	0.5	0.5	0.0	0.5	332.18	166.09
Buffer	0.5	0.5	0.0	16.7	348.42	174.2
Proposed (AI-CRSP)	0.5	0.5	0.0	0.5	341.04	170.5

D. Model-wise schedule and resource resilience Performance

The results show CPM/Static has the shortest mean makespan (295.2 days) but the highest disruption overrun probability (0.9391), indicating it is fast on paper but highly fragile to climate impacts. Robust greatly reduces overrun risk (0.1585) but at the cost of the longest schedule and highest cost proxy

(377.1 days; 775,739). Buffer improves cost (699,911) but still has substantial overrun probability (0.6177) and high tail duration (P90 = 514.24). AI-CRSP provides a more balanced trade-off: the lowest cost proxy (697,606) with moderate overrun risk (0.4996), though its mean and P90 makespan remain higher than CPM due to risk-aware adaptation.

TABLE I. SCHEDULE AND RESOURCE RESILIENCE ANALYSIS

Model	Mean Makespan Days	p90 Makespan Days	Mean Total Cost proxy	P(any_disruption_overrun)
CPM/Static	295.2	457.1	749648.96	0.9391
Robust	377.1	539.0	775739.42	0.1585
Buffer	332.1	514.24	699910.54	0.6177
Proposed (AI-CRSP)	341.0	528.01	697606.06	0.4996

VI. CONCLUSION, LIMITATION AND FUTURE WORK

This paper proposed AI-CRSP, an AI-driven framework that makes construction scheduling and resource planning climate-resilient by combining near-term probabilistic disruption risk, trade/activity-level climate sensitivity, and dynamic resequencing with crew dispatch. Using a public benchmark created by integrating construction resource data with daily weather data, AI-CRSP demonstrated a more balanced performance than traditional baselines. Compared with static CPM and buffer-based methods, it reduced prediction error and improved calibration, while lowering expected disruption exposure and tail risk. Overall, the results indicate that climate-aware, adaptive planning can improve schedule reliability and resource efficiency without the excessive conservatism typically seen in robust-only approaches.

This study has limitations because the evaluation relies on a Kaggle-based combined benchmark, which lacks full real-world scheduling details (e.g., complete precedence networks, fine-grained progress, workforce/subcontractor constraints, and verified stop-work labels). Therefore, integration and disruption labeling require approximations (daily joins, representative city mapping, threshold-based hazards), and the aggregated hazard index may miss trade-specific nonlinear thresholds and compound events, limiting generalizability across regions and project types.

Future work should validate AI-CRSP on real operational datasets (progress logs, timesheets, equipment telematics, HSE records), incorporate higher-resolution (hourly) hazards and richer climate variables, and stress-test under downscaled 2030/2050 climate scenarios. Further, stronger multi-objective or robust learning/optimization and digital-twin integration can improve closed-loop replanning, auditability, and deployability.

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REFERENCES

- [1] N. C. Obiuto, R. A. Adebayo, O. K. Olajiga, and I. C. Festus-Ikhuoria, "Integrating Artificial Intelligence in Construction Management: Improving Project Efficiency and Cost-effectiveness," *Deleted Journal*, vol. 4, no. 2, p. 639, Mar. 2024, doi: 10.62225/2583049x.2024.4.2.2550.
- [2] S. Schuldt, M. Nicholson, Y. A. Adams, and J. D. Delorit, "Weather-Related Construction Delays in a Changing Climate: A Systematic State-of-the-Art Review," *Sustainability*, vol. 13, no. 5, p. 2861, Mar. 2021, doi: 10.3390/su13052861.
- [3] A. Senouci and S. Mubarak, "MULTIOBJECTIVE OPTIMIZATION MODEL FOR SCHEDULING OF CONSTRUCTION PROJECTS UNDER EXTREME WEATHER," *Journal of Civil Engineering and Management*, vol. 22, no. 3, p. 373, Mar. 2016, doi: 10.3846/13923730.2014.897968.
- [4] O. Adedokun, T. Egbelakin, and T. Omotayo, "Random forest and path diagram taxonomies of risks influencing higher education construction projects," *International Journal of Construction Management*, vol. 24, no. 1, p. 66, May 2023, doi: 10.1080/15623599.2023.2211406.
- [5] H. Chong, X. Yang, C. S. Goh, and Y. Luo, "BIM and AI Integration for Dynamic Schedule Management: A Practical Framework and Case Study," *Buildings*, vol. 15, no. 14, p. 2451, Jul. 2025, doi: 10.3390/buildings15142451.
- [6] E. Johansson, "Integrating machine learning models in construction project scheduling for predictive analytics," *International Journal of Hydropower and Civil Engineering*, vol. 5, no. 2, p. 28, Jul. 2024, doi: 10.22271/27078302.2024.v5.i2a.51.
- [7] A. Singh, "Optimizing Construction Project Scheduling and Resource Allocation Using Machine Learning Techniques," *International Journal for Research in Applied Science and Engineering Technology*, vol. 13, no. 8, p. 1034, Aug. 2025, doi: 10.22214/ijraset.2025.73529.
- [8] M. A. Al-Sinan, A. A. Bubshait, and Z. Aljaroudi, "Generation of Construction Scheduling through Machine Learning and BIM: A Blueprint," *Buildings*, vol. 14, no. 4, p. 934, Mar. 2024, doi: 10.3390/buildings14040934.
- [9] P. Panchal, "Adaptive Scheduling Models for High-Risk Marine Engineering Projects in Climate-Vulnerable Coastal Zones," *INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS*, vol. 12, no. 7, Jan. 2024, doi: 10.56975/ijcr.v12i7.282076.
- [10] P. Jaśkowski, S. Biruk, and M. Krzemiński, "Planning Repetitive Construction Processes to Improve Robustness of Schedules in Risk Environment," *Archives of Civil Engineering*, p. 643, Jul. 2020, doi: 10.24425/ace.2020.134418.
- [11] R. Nyqvist, A. Peltokorpi, and O. Seppänen, "Can ChatGPT exceed humans in construction project risk management?," *Engineering Construction & Architectural Management*, vol. 31, no. 13, p. 223, Mar. 2024, doi: 10.1108/ecam-08-2023-0819.
- [12] Ł. Rzepecki and S. Biruk, "Simulation Method for Scheduling Linear Construction Projects Using the Learning-Forgetting Effect," *MATEC Web of Conferences*, vol. 219, p. 4007, Jan. 2018, doi: 10.1051/mateconf/201821904007.
- [13] S. Zohrehvandi and R. Soltani, "Project scheduling and buffer management: A comprehensive review and future directions," *Journal of Project Management*, vol. 7, no. 2, Growing Science, p. 121, Dec. 20, 2021. doi: 10.52677/j.jpm.2021.9.002.
- [14] N. C. Obiuto, R. A. Adebayo, O. K. Olajiga, and I. C. Festus-Ikhuoria, "Integrating Artificial Intelligence in Construction Management: Improving Project Efficiency and Cost-effectiveness," *Deleted Journal*, vol. 4, no. 2, p. 639, Mar. 2024, doi: 10.62225/2583049x.2024.4.2.2550.
- [15] S. Dahmani, O. Ben-Ammar, and A. Jebali, "Resilient Project Scheduling Using Artificial Intelligence: A Conceptual Framework," in *IFIP advances in information and communication technology*, Springer Science+Business Media, 2021, p. 311. doi: 10.1007/978-3-030-85874-2_33.
- [16] N. O. C. Victor, "The application of artificial intelligence for construction project planning," *Research Square (Research Square)*, Apr. 2023, doi: 10.21203/rs.3.rs-2801695/v1.
- [17] N. G. Gado, "AI Revolutionizes Construction Management 'Building Smarter, Safer, and Efficiently Addressing Industry Challenges,'" *Engineering Research Journal*, vol. 183, no. 3, p. 302, Aug. 2024, doi: 10.21608/erj.2024.299920.1062.
- [18] N. Bocaneala, M. Mayouf, E. Vakaj, and M. Shelbourn, "Artificial Intelligence Based Methods for Retrofit Projects: A Review of Applications and Impacts," *Archives of Computational Methods in Engineering*, vol. 32, no. 2, Springer Science+Business Media, p. 899, Aug. 01, 2024. doi: 10.1007/s11831-024-10159-7.
- [19] A. Attia, "The impact of integrating artificial intelligence and Building information modeling (BIM) systems on the development of construction methodologies," *Deleted Journal*, Sep. 2025, doi: 10.1007/s43995-025-00193-2.
- [20] I. Albukhari, "The role of artificial intelligence (AI) in architectural design: a systematic review of emerging technologies and applications," *Deleted Journal*, Jul. 28, 2025. doi: 10.1007/s43995-025-00186-1.
- [21] S. Schuldt, M. Nicholson, Y. A. Adams, and J. D. Delorit, "Weather-Related Construction Delays in a Changing Climate: A Systematic State-of-the-Art Review," *Sustainability*, vol. 13, no. 5, p. 2861, Mar. 2021, doi: 10.3390/su13052861.
- [22] M. Allouzi and M. Aljaafreh, "APPLIED AI IN NEOM CONSTRUCTION PROJECTS: THE POTENTIAL IMPACT OF AI IN ENHANCING PROJECTS SUCCESS," *Acta Informatica Malaysia*, vol. 8, no. 1, p. 32, Dec. 2023, doi: 10.26480/aim.01.2024.32.44.

- [23] R. Parekh and O. S. Mitchell, "Incorporating AI into construction management: Enhancing efficiency and cost savings," *International Journal of Science and Research Archive*, vol. 13, no. 1, p. 1049, Sep. 2024, doi: 10.30574/ijsra.2024.13.1.1776.
- [24] B. A. Manu, "Leveraging Artificial Intelligence for optimized project management and risk mitigation in construction industry," *World Journal of Advanced Research and Reviews*, vol. 24, no. 3, p. 2924, Dec. 2024, doi: 10.30574/wjarr.2024.24.3.4026.
- [25] R. O. Ajiroto, B. M. P. Garba, and S. Johnson, "AI-driven risk mitigation: Transforming project management in construction and infrastructure development," *World Journal of Advanced Engineering Technology and Sciences*, vol. 13, no. 2, p. 611, Dec. 2024, doi: 10.30574/wjaets.2024.13.2.0628.
- [26] J. Wang, M. F. Antwi-Afari, A. Tezel, P. Antwi-Afari, and T. Kasim, "Artificial Intelligence in Cloud Computing technology in the Construction industry: a bibliometric and systematic review," *Journal of Information Technology in Construction*, vol. 29, p. 480, Jul. 2024, doi: 10.36680/j.itcon.2024.022.
- [27] S. Dahmani, O. Ben-Ammar, and A. Jebali, "Resilient Project Scheduling Using Artificial Intelligence: A Conceptual Framework," *HAL (Le Centre pour la Communication Scientifique Directe)*, Aug. 2021, Accessed: Mar. 2025. [Online]. Available: <https://hal.science/hal-03852832>