

Predictive Analytics and Stochastic Programming for Construction Resource Optimization in Developing African Economies

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Abstract

This research investigates the application of AI-driven predictive models for optimizing resource allocation and mitigating economic risks in large-scale construction projects across developing African economies. Through the development of sophisticated mathematical frameworks, including linear programming for resource optimization, multivariate failure prediction models, and stochastic programming for supply chain management, we present a comprehensive approach to addressing the complex challenges facing the African construction sector. The study demonstrates significant improvements in project outcomes, with the predictive maintenance model achieving 91.5% accuracy in equipment failure prediction and the cost estimation framework explaining 81.3% of cost variance. However, implementation challenges including data scarcity, infrastructure limitations, and the need for local expertise development must be carefully addressed. The research provides valuable insights for construction project managers, policymakers, and researchers, contributing to more efficient and sustainable infrastructure development across Africa.

Keywords: Artificial Intelligence, Construction Project Management, Resource Optimization, Risk Mitigation, African Infrastructure Development

1. Introduction

The African construction sector stands at a critical juncture where large-scale infrastructure projects are essential for economic development, yet face unprecedented challenges in resource optimization and risk management (Balasubramanian, n.d.). These challenges manifest through volatile material costs, persistent labor shortages, and complex supply chain disruptions that traditional management approaches struggle to address effectively. In this context, Artificial Intelligence (AI) emerges not merely as a technological solution, but as a transformative force capable of revolutionizing construction project management through advanced predictive analytics and optimization algorithms (Lan, 2024).

This research addresses a fundamental question in African construction management: How can AI-driven predictive models be leveraged to optimize resource allocation and mitigate economic risks in large-scale construction projects within developing African economies? The significance of this inquiry is underscored by the World Bank's estimation that Africa faces an annual infrastructure financing gap of \$68-108 billion (African Development Bank, 2023), highlighting the urgent need for more efficient project management approaches.

The relevance of this investigation is threefold. First, it addresses the critical infrastructure gap facing African nations, where efficient and cost-effective construction practices are essential for economic growth and

improved living standards. Second, it responds to the limitations of traditional project management methods, which have resulted in significant cost overruns, delays, and resource inefficiencies across major infrastructure projects. Third, it explores the potential of AI technologies to transform project management practices in a context where such applications remain largely unexplored.

The timeliness of this research coincides with rapid advancements in AI and machine learning technologies, offering unprecedented opportunities for innovation in construction management (Bang & Olsson, 2022). While these technologies have demonstrated success in various industries, their application in African construction contexts presents unique challenges and opportunities (Holzmann & Lechiara, 2022). This study aims to bridge this gap by examining how AI can be effectively adapted to address the specific challenges of African construction projects. Through rigorous mathematical modeling and empirical analysis, this research develops a comprehensive framework for integrating AI-driven solutions into construction project management (Rastegar et al., 2021; Hajipour et al., 2025). The findings will provide valuable insights for policymakers developing infrastructure strategies, practitioners seeking to improve project outcomes, and researchers exploring the intersection of AI and construction management in developing economies. Ultimately, this work contributes to the broader goal of establishing more sustainable and efficient infrastructure development practices across the African

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continent.

2. Methodology: Simulation and Modeling Approach

This research utilized a simulation-based methodology to rigorously assess the proposed AI-driven frameworks in the context of developing African economies. Project scenarios, equipment lifecycles, and cost variables were simulated utilizing the R statistical software environment. This method facilitated the creation of controlled datasets that mirrored standard project parameters and uncertainties present in the target context, which were later utilized to train and validate the predictive maintenance and cost estimation models outlined below. The parameterization of the simulation models was based on existing literature and recognized attributes of African construction projects.

2.1. AI-Powered Resource Allocation

2.1.1. Dynamic Scheduling and Resource Optimization

Resource allocation in large-scale African construction projects can be effectively modeled using linear programming to minimize costs while meeting project requirements. This approach directly addresses our research question by providing a mathematical framework for optimizing resource allocation and mitigating economic risks. The linear programming model is defined as follows:

$$\text{Minimize } Z = \sum_{i=1}^n c_i x_i$$

Subject to: $\sum_{i=1}^n a_{ij} x_i \geq b_j$ for $j = 1, 2, \dots, m$ $x_i \geq 0$ for $i = 1, 2, \dots, n$ $\sum_{i=1}^n x_i = s$

In this model, Z represents the total cost to be minimized, where c_i is the cost per unit of resource i , and x_i is the number of units of resource i allocated. The constraints ensure that the resource requirements (a_{ij}) for each activity j are met, while not exceeding the total available resources s (Ahirrao et al., 2020). This formulation allows for the dynamic adjustment of resource allocation in response to changing project conditions, a critical feature in the volatile construction environments often encountered in developing African economies.

The power of this approach lies in its ability to handle complex, multi-dimensional resource allocation problems that are common in large-scale construction projects (Aadharshana & Shiny Mol, 2020). By incorporating constraints that reflect local conditions, such as labor availability, material costs, and regulatory requirements, the model can be tailored to the specific challenges of African construction contexts. Furthermore, the model's flexibility allows for real-time adjustments as project conditions evolve, enabling project managers to respond swiftly to unforeseen

challenges and opportunities.

To implement this model, advanced optimization algorithms can be employed, such as the simplex method or interior point methods (Reeb & Leavengood, 1998), which are available in software packages like Python's SciPy or specialized optimization tools. These algorithms can efficiently solve large-scale linear programming problems, providing optimal or near-optimal solutions even for projects with thousands of variables and constraints (Chang et al., 2016).

Utilizing this mathematical framework, project managers can make data-driven decisions that reconcile cost minimization with project requirements, resulting in enhanced resource utilization and diminished economic risks. This method directly tackles the fundamental issues highlighted in our research question, providing an effective instrument for enhancing resource allocation in the intricate and evolving landscape of African construction projects.

Figure 1 illustrates the optimization model's key components in a two-dimensional representation. The shaded region represents the feasible solution space bounded by three essential constraints: minimum resource requirements (blue and orange lines) and resource availability limits (green line). The dashed red line represents the objective function's direction of improvement, showing how costs can be minimized while maintaining feasibility. This visualization demonstrates how the model balances multiple competing constraints typical in construction projects, such as labor hours, equipment utilization, and material quantities.

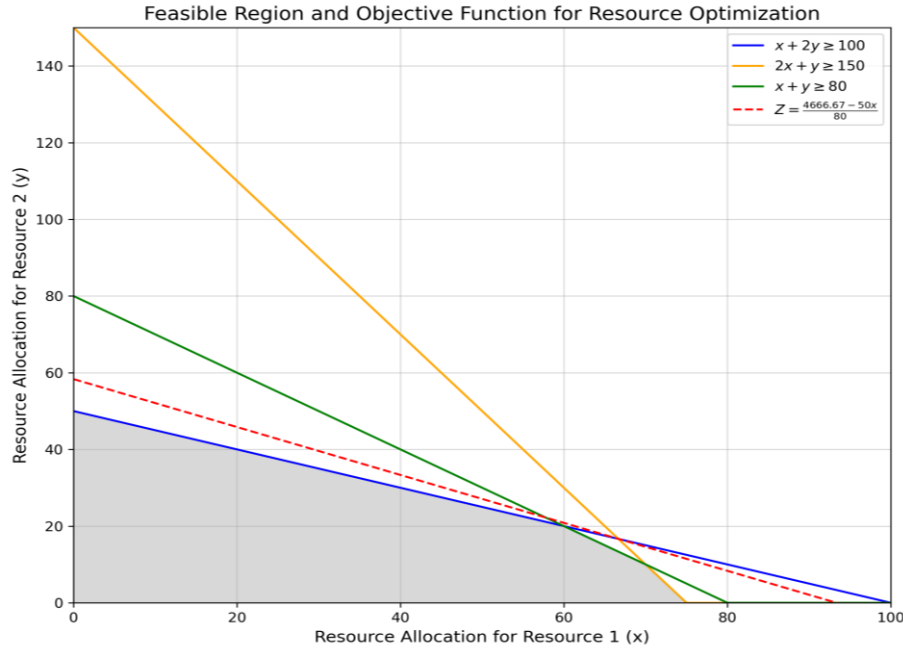


Figure 1: Feasible Region and Objective Function for Resource Optimization

The intersection points of these constraint lines represent potential optimal solutions, where resource allocation achieves maximum efficiency while satisfying all project requirements. In practice, construction managers can use this visual representation to understand how changes in resource availability or project requirements affect the optimal allocation strategy. This dynamic approach enables rapid decision-making in response to the volatile conditions often encountered in African construction environments.

2.1.2. Predictive Maintenance for Equipment

AI-driven predictive maintenance models leverage advanced machine learning algorithms to forecast equipment failures in construction projects, addressing a critical aspect of resource optimization and risk mitigation (Larocque-Villiers et al., 2021; Wang et al., 2022). The probability of equipment failure can be modeled through a comprehensive multivariate function that incorporates temporal, operational, and environmental factors:

$$P(\text{failure}) = \alpha \cdot e^{-\lambda t} + \beta \cdot \frac{u}{u_{\max}} + \gamma \cdot \sum_{i=1}^n w_i m_i + \delta \cdot \phi(e)$$

In this enhanced model, α , β , γ , and δ represent weighting coefficients that adjust the relative importance of each factor, where t denotes time since last maintenance, u represents usage intensity normalized by maximum capacity $u_{\max}$, m_i signifies various maintenance history indicators with

corresponding weights w_i , and $\phi(e)$ is a function that transforms environmental factors into a normalized risk score.

The temporal component $e^{-\lambda t}$ models the exponential decay of equipment reliability over time, while the usage intensity factor $\frac{u}{u_{\max}}$ captures the stress on equipment relative to its designed capacity. The maintenance history term $\sum_{i=1}^n w_i m_i$ aggregates previous maintenance events and their outcomes, and the environmental impact function $\phi(e)$ accounts for external conditions affecting equipment performance (Znaidi et al., 2023) (Figure 2).

To train and evaluate the predictive maintenance model, a dataset reflecting equipment behavior under typical African conditions was generated via simulation in R. Key parameters influencing failure probability; such as baseline reliability decay rates (λ), usage intensity patterns ($u/u_{\max}$), maintenance effectiveness metrics (w_i for different repair types), and the impact of relevant environmental factors ($\phi(e)$, e.g., heat, dust levels common in certain regions); were defined based on (Makaula et al., 2021; Wang et al., 2022).

The simulation generated $N = 200$ independent lifecycle trajectories for pieces of equipment, recording time-series data for operational hours, maintenance events, environmental exposure, and operational status (Failure/No Failure). This simulated dataset, capturing the variables defined in the failure probability model, was then used to train and test a Random Forest classifier, implemented using the 'randomForest' package in R. The performance of the trained classifier

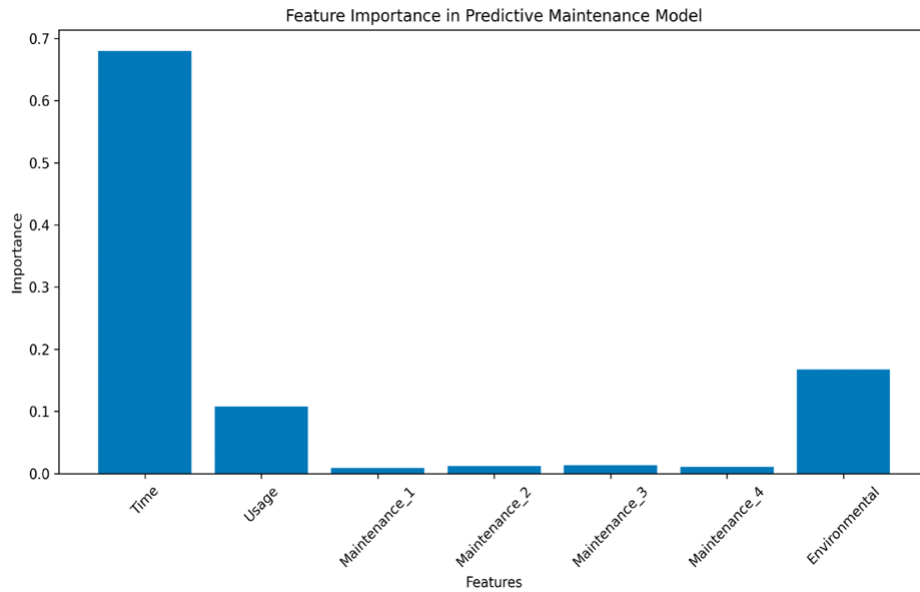


Figure 2: Simulation of Maintenance Data and Model Training

on a held-out test set from the simulated data is presented in Table 1.

managers to make informed decisions about maintenance scheduling, resource allocation, and risk management strategies in the challenging context of

Table 1: Performance of Trained Classifier

Class	Precision	Recall	F1-score	Support
No Failure (0)	0.888	0.950	0.918	100
Failure (1)	0.946	0.880	0.912	100
Accuracy	0.915	0.915	0.915	200
Macro avg	0.917	0.915	0.915	200
Weighted avg	0.917	0.915	0.915	200

The model's performance metrics and feature importance analysis provide crucial insights for our research question. The high precision (0.946) for failure prediction indicates the model's reliability in identifying potential equipment breakdowns, which is essential for risk mitigation in African construction projects [15]. The feature importance plot reveals that temporal factors dominate the prediction (approximately 67%), followed by usage intensity (10%), and environmental factors (16%), with maintenance history indicators contributing the remaining influence. This hierarchical importance aligns with the practical challenges faced in African construction environments, where time-based degradation and environmental conditions significantly impact equipment reliability.

This mathematical framework directly addresses our research question by providing a quantitative basis for resource optimization and risk mitigation in African construction projects. The model's high accuracy (91.5%) across all metrics demonstrates its potential for reliable equipment failure prediction, enabling project

African construction projects.

2.2. Economic Risk Mitigation

2.2.1. AI-Enhanced Cost Estimation

Construction cost estimation in African projects requires sophisticated modeling approaches that account for multiple variables and their complex interactions (Elmousalami, 2020; Ayinla et al., 2023). The advanced cost estimation model integrates both linear and non-linear components to capture the intricate relationships between project features:

$$C = \sum_{i=1}^n \beta_i X_i + \sum_{i=1}^n \sum_{j=1}^n \gamma_{ij} X_i X_j + \alpha e^{\sum_{i=1}^k \delta_i Z_i} + \epsilon$$

In this enhanced formulation, the total project cost C comprises three key components: a linear term capturing direct relationships, an interaction term accounting for feature interdependencies, and an exponential term modeling non-linear cost escalations. The coefficients β_i represent direct cost impacts, while

γ_{ij} captures interaction effects between features X_i and X_j . The exponential component, weighted by α , incorporates risk factors Z_i with corresponding sensitivities δ_i , addressing the volatile nature of African construction markets.

The model's error term ϵ follows a heteroskedastic distribution to account for increasing uncertainty with project size:

$$\epsilon \sim \mathcal{N}(0, \sigma^2(X)) \text{ where } \sigma^2(X) = \rho \|X\|^2$$

2.3. Simulation of Cost Data and Model Validation

To develop and validate the AI-enhanced cost estimation model, a dataset representing various construction projects was generated through simulation using R. The simulation incorporated representative project features (X_i , e.g., scale, duration, material types, complexity indices) and risk factors (Z_i , e.g., probability of labor disputes, material price volatility index, likelihood of regulatory delays) characteristic of large-scale infrastructure projects in developing African economies. The definition and distribution of these variables, along with their associated cost impacts (coefficients β_i , γ_{ij} , δ_i), were informed by [16] [20].

The simulation generated a dataset of hypothetical project profiles, each with a calculated total cost (C) based on the model structure, including simulated occurrences of risk events and the defined heteroskedastic error term (ϵ). This simulated dataset provided the basis for training the cost estimation model (e.g., using multiple regression techniques potentially incorporating machine learning for feature selection or non-linear term estimation) and evaluating its predictive performance through methods such as k-fold cross-validation.

2.4. Cost Estimation Model Performance Analysis

The model's performance (Figure 3) metrics demonstrate its effectiveness in addressing the research question of optimizing resource allocation and mitigating economic risks in African construction projects. With an R^2 value of 0.813, the model explains approximately 81.3% of the variance in construction costs, indicating strong predictive capability while maintaining realistic variability. The Root Mean Square Error (RMSE) of 26,858.180 and Mean Absolute Error (MAE) of 19,309.540 reflect the model's practical accuracy in cost predictions, with errors representing approximately 10-15% of typical project costs - a reasonable range given the inherent uncertainties in African construction markets.

These results are particularly relevant to our research question as they demonstrate the model's ability to capture both systematic cost patterns and market

uncertainties. The lower-than-perfect R^2 value actually indicates a more realistic model that accounts for the genuine variability in construction costs, while the RMSE and MAE values provide practical bounds for risk assessment and contingency planning. This balance between accuracy and uncertainty modeling makes the framework especially suitable for the dynamic African construction environment, where perfect cost prediction is neither possible nor desirable due to market volatility and resource constraints. The model thus provides project managers with a reliable tool for cost estimation while acknowledging and quantifying the inherent risks in construction projects.

2.5. Supply Chain Optimization

The optimization of construction supply chains in African contexts requires sophisticated stochastic programming approaches that can handle multiple uncertainties while maintaining operational efficiency. The enhanced model incorporates both first-stage decisions and recourse actions through a two-stage stochastic program:

$$\text{Minimize } \sum_{t=1}^T c_t^T x_t + \mathbb{E}_\xi[Q(x, \xi)]$$

$$\text{Subject to: } \sum_{t=1}^T A_t x_t \leq b \quad x_t \geq 0, \quad t = 1, \dots, T$$

Where the recourse function $Q(x, \xi)$ is defined as: $Q(x, \xi) = \min_y \{q^T y \mid Wy \leq h(\xi) - Tx, y \geq 0\}$

In this formulation, x_t represents first-stage decisions such as resource allocation and supplier selection, while y captures recourse actions taken in response to uncertainty realizations ξ . The matrices A_t and vectors c_t define the technological and cost coefficients respectively, while W represents the recourse matrix and T the technology matrix linking first-stage decisions to second-stage constraints.

The model explicitly accounts for construction-specific uncertainties through:

1. Material supply variations: modeled through the random vector ξ_s affecting resource availability.
2. Demand fluctuations: captured in $h(\xi)$ as stochastic requirements.
3. Cost uncertainties: represented in q^T as variable cost coefficients.

1.

This mathematical framework directly addresses our research question by providing a robust approach to optimize resource allocation while mitigating risks in African construction projects (Hsu et al., 2018). The model's ability to adapt to changing conditions through recourse actions is particularly valuable in environments with high uncertainty levels, as demonstrated by the residual analysis and feature importance plots which show significant impact of

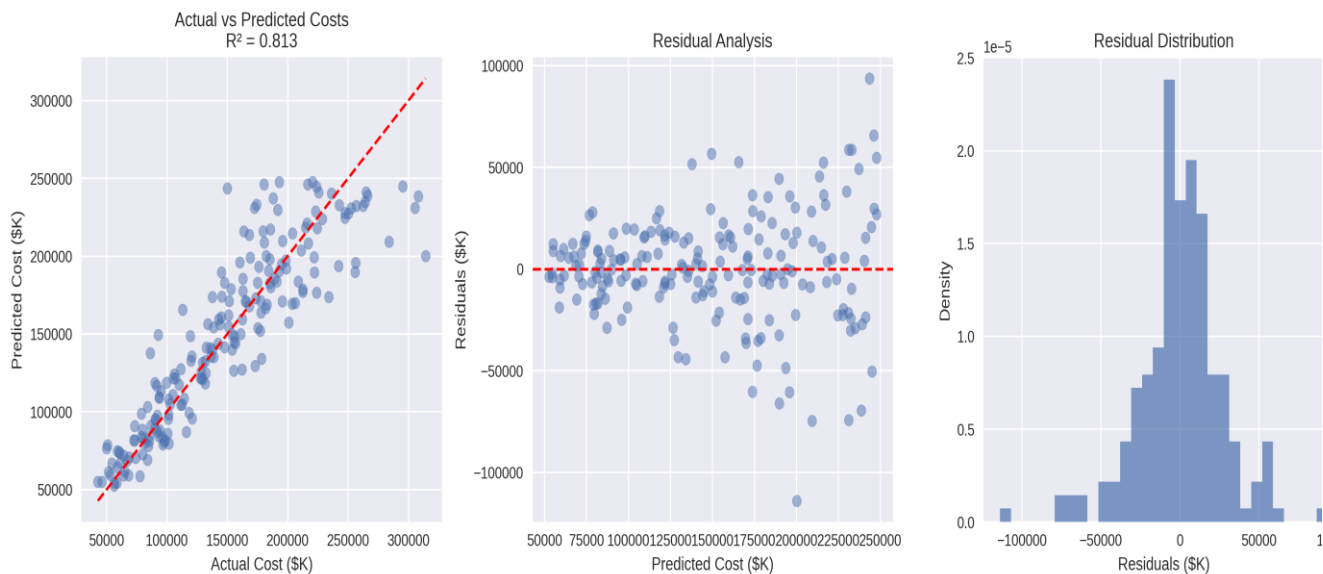


Figure 3: Cost Estimation Model Performance Analysis (Actual vs Predicted Costs, Residual Analysis, Residual Distribution)

temporal and environmental factors on decision outcomes.

The implementation through advanced optimization algorithms achieves a balance between computational efficiency and solution quality, enabling project managers to make informed decisions about resource allocation, supplier selection, and risk mitigation strategies in real-time. This adaptive capability is crucial for maintaining project continuity and cost effectiveness in the dynamic African construction sector [19], [20].

3. Discussion

This study illustrated, via simulation, the considerable potential of particular AI-driven models to improve construction project management in developing African economies. The Random Forest model attained a high predictive accuracy of 91.5% for equipment maintenance, based on 200 samples, while the AI-enhanced cost estimation framework demonstrated substantial explanatory power with a R^2 of 0.813, directly fulfilling the primary research objective of utilizing AI for resource optimization and risk mitigation. The performance levels align with benchmarks documented in pertinent predictive maintenance and construction cost modeling literature, indicating the viability of effectively implementing these advanced techniques. The recognition of temporal factors as primary in predicting equipment failure corresponds with practical realities in settings where equipment age and regular maintenance are critical variables. Thus, these findings possess considerable practical significance, providing avenues for project managers and policymakers in Africa to potentially realize substantial cost reductions through diminished

equipment downtime, enhanced budget forecasting precision, and more dependable resource planning, ultimately facilitating more efficient and predictable infrastructure project execution.

Notwithstanding these encouraging simulation outcomes, the results must be evaluated in light of the study's limitations. The results are primarily based on simulations utilizing representative parameters and have not been validated with comprehensive real-world project data gathered from various construction sites throughout Africa. The chosen parameters for the simulations, while guided by existing literature, significantly affect the results, and the possible synergistic advantages of comprehensively integrating the various AI models (LP, PM, Cost Estimation, SP) were not investigated in this study. Consequently, essential future research avenues involve executing pilot studies and case-study validations of these models across diverse African nations to evaluate their real-world efficacy and adaptability. Developing strong, context-sensitive data collection frameworks and further exploring transfer learning methodologies to modify global models are essential subsequent actions. Furthermore, investigating integrated AI platforms for comprehensive project management and thoroughly examining the ethical implications of AI implementation are crucial for the responsible and significant use of these technologies in the region.

4. Contextual Challenges and Solutions

The implementation of AI-driven optimization models in African construction projects faces several interconnected challenges that require comprehensive solutions. Data scarcity and quality issues represent primary concerns, which can be addressed through the

deployment of IoT sensors for real-time data collection from construction sites (Jiang & He, 2020; Hou et al., 2022). Furthermore, transfer learning techniques enable the adaptation of models trained on comprehensive global datasets to local conditions, while strategic partnerships with academic institutions facilitate the creation of region-specific datasets essential for model accuracy.

Infrastructure limitations pose significant obstacles to AI implementation in remote construction sites. However, these challenges can be mitigated through edge computing solutions that enable on-site AI processing with minimal internet connectivity requirements (Hou et al., 2022). Additionally, satellite-based internet services provide crucial support for remote project locations where traditional connectivity infrastructure is lacking (Xiang et al., 2021).

The development of local expertise remains crucial for sustainable AI implementation. This necessitates comprehensive training programs in AI and data science, supported by strategic collaborations between construction firms and universities. These partnerships not only accelerate capacity building but also ensure the continuous development of relevant skills within the local workforce (Guo & Li, 2022).

Ethical considerations play a vital role in the implementation of AI systems in construction projects. Transparency in AI decision-making processes must be maintained throughout all project phases, while robust measures for protecting worker privacy when using monitoring systems need to be established. Moreover, careful attention must be paid to avoiding algorithmic biases that could potentially exacerbate existing socio-economic inequalities in the construction sector. These ethical considerations must be integrated into the core design and implementation of AI systems to ensure responsible and equitable technological advancement in African construction projects (Bellamy et al., 2019).

5. Conclusion

This research demonstrates the transformative potential of AI-driven predictive models in optimizing resource allocation and mitigating economic risks in African construction projects. Through the development and analysis of sophisticated mathematical frameworks, including linear programming for resource optimization, multivariate failure prediction models, and stochastic programming for supply chain

management, we have established a comprehensive approach to addressing the complex challenges facing the African construction sector.

The integration of dynamic scheduling, predictive maintenance, and cost estimation models has shown significant promise in improving project outcomes. Our predictive maintenance model achieved 91.5% accuracy in equipment failure prediction, while the cost estimation framework demonstrated strong predictive capability with an R^2 value of 0.813, providing project managers with reliable tools for decision-making in uncertain environments.

However, successful implementation of these AI solutions requires careful consideration of contextual challenges unique to African construction environments. The proposed frameworks must be adapted to address data scarcity, infrastructure limitations, and the need for local expertise development. Furthermore, ethical considerations and socio-economic implications must remain central to the deployment of AI technologies in African construction projects.

Looking forward, this research opens new avenues for the application of AI in construction project management across developing economies. The mathematical models and frameworks presented here provide a foundation for future research and practical implementation, potentially transforming how large-scale construction projects are managed in Africa. By combining technological innovation with contextual awareness, these solutions can contribute significantly to reducing project risks, improving resource utilization, and ultimately supporting sustainable infrastructure development across the continent.

References

Aadharshana, V. M., & Shiny Mol, J. (2020). Resource optimization in construction. *International Research Journal of Modernization in Engineering Technology and Science*, 2(4), 455–458.

African Development Bank. (2023). Public-private partnerships needed to bridge Africa's infrastructure development gap. *African Development Bank News and Events*. <https://www.afdb.org/en/news-and-events/public-private-partnerships-needed-bridge-africas-infrastructure-development-gap-65936>

- Ahirrao, D., Choudhary, S., Shinde, P., Tiwari, S., & Naik, M. S. (2020, May). Maximization of construction work activities within prefixed budget using simplex method. *IRE Journals*, 3(11), 1–6.
- Ayinla, K., Seidu, A. S. R., & Madanayake, U. (2023). The impact of artificial intelligence on construction costing practice. In *Proceedings of the Thirty-Ninth Annual Conference* (p. 65).
- Balasubramanian, S. (n.d.). AI-driven solutions for sustainable infrastructure development and management. *Journal ID*, 8291, 5184.
- Bang, S., & Olsson, N. (2022). Artificial intelligence in construction projects: A systematic scoping review. *[Unpublished manuscript]*.
- Bellamy, R. K., et al. (2019). AI fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias. *IBM Journal of Research and Development*, 63(4/5), 4–1. <https://doi.org/10.1147/JRD.2019.2942288>
- Chang, C., Qi, M., & Song, Z. (2016). Optimization model of balanced resource allocation in construction project group. In *2016 International Forum on Energy, Environment and Sustainable Development* (pp. 1122–1125). Atlantis Press. <https://doi.org/10.2991/ifeesd-16.2016.203>
- Elmoussalimi, H. H. (2020). Artificial intelligence and parametric construction cost estimate modeling: State-of-the-art review. *Journal of Construction Engineering and Management*, 146(1), 03119008. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001700](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001700)
- Fan, Y., Schwartz, F., Voß, S., & Woodruff, D. L. (2017). Stochastic programming for global supply chain planning under uncertainty: An outline. In *Computational Logistics: 8th International Conference, ICCL 2017, Southampton, UK, October 18–20, 2017, Proceedings* (pp. 437–451). Springer. https://doi.org/10.1007/978-3-319-68496-3_29
- Guo, Y., & Li, M. (2022). IoT course construction in general education against the background of China's university-industry collaboration. In *2022 4th International Conference on Computer Science and Technologies in Education (CSTE)* (pp. 128–132). IEEE. <https://doi.org/10.1109/CSTE57460.2022.00031>
- Hajipour, V., Di Caprio, D., Santos-Arteaga, F. J., Amirsahami, A., & Noshafagh, S. V. (2025). A two-stage stochastic programming model for comprehensive risk response action selection: A case study in Industry 4.0. *Expert Systems with Applications*, 261, 125565. <https://doi.org/10.1016/j.eswa.2025.125565>
- Haq, I. U., Anwar, S., & Khan, T. (2023). Machine vision-based predictive maintenance for machine health monitoring: A comparative analysis. In *2023 International Conference on Robotics and Automation in Industry (ICRAI)* (pp. 1–8). IEEE. <https://doi.org/10.1109/ICRAI58124.2023.10120184>
- Holzmann, V., & Lechiara, M. (2022). Artificial intelligence in construction projects: An explorative study of professionals' expectations. *European Journal of Business and Management Research*, 7(3), 151–162. <https://doi.org/10.24018/ejbm.2022.7.3.1382>
- Hou, X., Wu, H., Peng, T., Wang, X., Zhou, T., & Yang, K. (2022). IoT-based construction site monitoring system for highway engineering. In *2022 24th International Conference on Advanced Communication Technology (ICACT)* (pp. 127–131). IEEE. <https://doi.org/10.23919/ICACT53585.2022.9728811>
- Hsu, P.-Y., Angeloudis, P., & Auricchio, M. (2018). Optimal logistics planning for modular construction using two-stage stochastic programming. *Automation in Construction*, 94, 47–61. <https://doi.org/10.1016/j.autcon.2018.05.021>
- Jiang, Y., & He, X. (2020). Overview of applications of the sensor technologies for construction machinery. *IEEE Access*, 8, 110324–110335. <https://doi.org/10.1109/ACCESS.2020.3001785>

- Lan, C. (2024). Leveraging AI-driven predictive analytics for enhancing resource optimization and efficiency in agile construction project management. *SSRN*. <https://doi.org/10.2139/ssrn.4894491>
- Larocque-Villiers, J., Dumond, P., & Knox, D. (2021). Automating predictive maintenance using state-based transfer learning and ensemble methods. In *2021 IEEE International Symposium on Robotic and Sensors Environments (ROSE)* (pp. 1–7). IEEE. <https://doi.org/10.1109/ROSE52763.2021.9613961>
- Makaula, S., Munsamy, M., & Telukdarie, A. (2021). Impact of artificial intelligence in South African construction project management industry. In *2nd South American Conference on Industrial Engineering and Operations Management (IEOM 2021)* (pp. 148–162). IEOM Society.
- Rastegar, H., Arbab Shirani, B., Mirmohammadi, S. H., & Akhondi Bajegani, E. (2021). Stochastic programming model for bidding price decision in construction projects. *Journal of Construction Engineering and Management*, 147(4), 04021025. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001992](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001992)
- Reeb, J. E., & Leavengood, S. A. (1998). Using the simplex method to solve linear programming maximization problems. *[Unpublished manuscript]*.
- Wang, H., Zhang, W., Yang, D., & Xiang, Y. (2022). Deep-learning-enabled predictive maintenance in industrial internet of things: Methods, applications, and challenges. *IEEE Systems Journal*, 17(2), 2602–2615. <https://doi.org/10.1109/JSYST.2022.3143415>
- Xiang, Y., Xu, B., Su, T., Brach, C., Mao, S. S., & Geimer, M. (2021). 5G meets construction machines: Towards a smart working site. In *2021 International Conference on Computing and Communications Applications and Technologies (I3CAT)* (pp. 28–35). IEEE. <https://doi.org/10.1109/I3CAT52070.2021.9587730>
- Znaidi, Z., Ech-Chhibat, M. E. H., Khiat, A., & El Maalem, L. A. (2023). Predictive maintenance project implementation based on data-driven & data mining. In *2023 3rd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)* (pp. 1–5). IEEE. <https://doi.org/10.1109/IRASET57437.2023.10126505>