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AI-Driven Optimization of Logistics and Open-Pit Mining Fleet Operations: Integrative Architectures, Predictive Analytics, and Emerging Connectivity Paradigms

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Abstract: This article synthesizes theoretical foundations, methodological approaches, and practical implications for AI-driven optimization of logistics systems and open-pit mining fleet operations. Building strictly upon the provided literature, it constructs a comprehensive conceptual framework that integrates ensemble machine learning for cost optimisation in commercial logistics, AI-driven predictive analytics for pharmaceutical procurement and supply centralization, high-bandwidth communications enabling real-time routing and delivery (6G), remote sensing methods for urban and non-urban point extraction, last-mile delivery strategies including drone integration, and advanced discrete-event and evolutionary optimisation methods for truck-shovel allocation and dispatch in mining. The structured analysis articulates problem formulations, proposes method-of-methods combinations (ensemble learning + discrete-event simulation + multi-objective evolutionary algorithms), and explicates evaluation criteria focused on economic, operational, and sustainability outcomes. Results are described qualitatively through descriptive analysis that translates algorithmic outputs into operational decisions, and implications are interpreted across multiple levels: strategic procurement and centralization effects on drug availability and health outcomes, tactical fleet scheduling and energy efficiency, and operational routing and last-mile feasibility under emerging connectivity infrastructures. Limitations, counter-arguments, and future research priorities are examined in depth, emphasising the importance of validation, explainability, and system-of-systems thinking when deploying AI in safety- and cost-critical domains. The article concludes with an integrated set of recommendations for researchers and practitioners seeking to design, validate, and scale AI-enabled logistics and mining fleet systems that balance efficiency, robustness, and ethical transparency.

Keywords: AI ensemble learning; logistics cost optimisation; predictive analytics; truck-shovel allocation; last-mile delivery; 6G connectivity; remote sensing

Introduction

The convergence of artificial intelligence, novel communication infrastructures, and advanced optimisation algorithms is reshaping the theoretical and practical landscape of logistics and heavy-asset operations. Contemporary logistics systems — from global pharmaceutical supply chains to urban last-mile delivery networks — demand methods that can jointly optimise cost, timeliness, and risk under deep uncertainty. Simultaneously, open-pit mining operations confront complex dynamic scheduling problems where truck-shovel dispatch efficiency has cascading effects on productivity, fuel consumption, and operational costs. Recent progress in ensemble machine learning approaches, predictive analytics for centralized procurement, high-speed communication architectures, remote sensing extraction methodologies, and sophisticated optimisation algorithms provides a rare opportunity to articulate an integrative research agenda that connects these strands into coherent, implementable solutions.

A central motivating problem is the tension between centralization and decentralization in supply systems, and the corresponding trade-offs between efficiency gains and systemic fragility. Centralized procurement and logistics can leverage scale effects and predictive analytics to lower unit costs and improve availability, but may induce distributional vulnerabilities if forecasting fails or if transport networks are disrupted (Anthony et al., 2024). At the operational level of fleet management, machine learning-enabled predictive maintenance and scheduling strategies promise reductions in downtime and fuel usage but must be reconciled with real-world constraints such as road deterioration, safety margins, and environmental impacts (Patil & Deshpande, 2025; Meneses & Sepúlveda, 2023).

The literature provided for this synthesis is both multidisciplinary and thematically complementary. Yaiprasert and Hidayanto (2024) demonstrate how AI-powered ensemble machine learning can be applied to optimise cost strategies in logistics businesses, providing a methodological anchor for cost-focused decision-making. Anthony et al. (2024) contextualize the economic and clinical effects of centralizing pharmaceutical supply chains, illustrating how AI-driven predictive analytics can shape prices, availability, and health outcomes. Advances in connectivity and real-time routing, exemplified by conceptual work on 6G-enabled logistics, promise ultra-low latency coordination that can transform routing, resourcing, and last-mile execution (Sauvola et al.). Shuaibu et al. (2025) review last-mile delivery optimisation strategies including drone integration. Ajani (2018) provides remote sensing techniques for extracting urban versus non-urban point data — crucial for accurate geospatial modelling. For heavy-asset operations, a suite of optimisation and simulation studies explores truck-shovel allocation, discrete-event modelling of road deterioration impacts, and multi-objective evolutionary algorithms for dispatching (Benlaajili et al., 2020; Alexandre et al., 2018; Ristovski et al., 2017; Zhang & Xia, 2015; Meneses & Sepúlveda, 2023).

Despite these advances, notable gaps remain. There is limited cross-domain synthesis that unites ensemble learning-based cost optimisation, predictive analytics for centralization impacts, connectivity-enabled real-time routing, remote sensing geodata extraction, drone-enabled last-mile logistics, and robust optimisation for mining fleet dispatch into a single, operationally coherent framework. Equally, the literature often treats methodological advances in isolation, leaving open questions about system integration, real-world validation, and governance constraints (explainability, safety, procurement policy). Addressing these gaps requires a method-of-methods approach that foregrounds modularity, interpretability, and staged validation.

This article responds by producing an integrative, publication-ready treatment of AI-driven optimisation for logistics and open-pit mining fleets. It outlines theoretical underpinnings, presents a detailed, text-based methodology that combines ensemble learning, predictive analytics, discrete-event simulation, and evolutionary optimisation, and provides descriptive results and a deep interpretive discussion of limitations, ethical considerations, and future research pathways. Throughout, claims and conceptual moves are anchored to the provided literature.

Methodology

The methodological architecture proposed here is deliberately integrative. Rather than offering a single algorithmic recipe, it prescribes a layered framework in which ensemble machine learning, predictive analytics, communications-enabled routing, geospatial extraction, last-mile modalities, and optimisation for heavy-asset dispatch interplay. The methodology is organised as follows: (1) problem specification and objectives; (2) data schema and geospatial preprocessing; (3) learning and predictive modules; (4) discrete-event simulation for operational validation; (5) multi-objective evolutionary optimisation for scheduling and dispatch; (6) connectivity and actuation considerations; and (7) evaluation metrics and validation procedures. Each component is elaborated below using exclusively descriptive exposition and rigorous cross-referencing to the provided works.

Problem specification and objectives

The central research problems addressed are: (a) how to reduce total logistics cost while maintaining or improving service levels in commercial and pharmaceutical supply chains; (b) how to design resilient procurement strategies when centralization is considered; (c) how to optimise last-mile delivery routes and modes (including drones) under connectivity constraints; and (d) how to schedule heavy-asset operations (truck-shovel allocation in open-pit mines) to maximize throughput while minimizing fuel consumption and accounting for road deterioration. Objectives are therefore multi-dimensional: minimise cost per delivered unit, maximise availability (especially critical drugs), reduce energy use and emissions, and maintain operational robustness.

Data schema and geospatial preprocessing

High-quality inputs are critical for any AI-driven system. For logistics cost optimisation and procurement forecasting, data types include historical demand time-series, procurement lead times, supplier reliability metrics, inventory levels, pricing records, transportation costs, and clinical outcomes (for pharmaceutical use-cases). For routing and last-mile planning, geospatial data, road network topologies, and node-level demand points (urban vs non-urban) are essential. Ajani (2018) provides a validated approach for extracting and validating databases that distinguish urban from non-urban points via remote sensing techniques, which supports demand localization and route feasibility assessment (Ajani, 2018). For open-pit mining, relevant datasets contain truck fleet sizes and capacities, shovel availability schedules, road segment conditions and gradients, historical fuel consumption rates, and discrete event logs of loading/unloading cycles (Meneses & Sepúlveda, 2023; Awuah-Offei et al., 2012).

Geospatial preprocessing relies on remote sensing outputs (Ajani, 2018) to tag demand points and road qualities. This tagging supports differentiated routing rules (urban last-mile vs rural long-haul) and enables fine-grained simulation of truck traversal times and wear. The process includes feature extraction (e.g., land cover, built-up indices), point classification (urban/non-urban), and validation against ground-truth samples when available. The output is a normalized geospatial database that integrates with supply chain, procurement, and fleet datasets.

Learning and predictive modules

The central analytical engine for cost optimisation is an ensemble machine learning architecture. Yaiprasert and Hidayanto (2024) demonstrate how AI-powered ensemble methods achieve superior predictive performance for cost-sensitive tasks in logistics compared to single-model baselines. The ensemble approach uses a heterogeneous mix of learners (e.g., gradient-boosted trees, random forests, and regularized linear models) combined via stacking or blending to reduce variance and bias while preserving interpretability via model-agnostic explanation tools. In the context of procurement and centralized purchasing models, the predictive analytics module forecasts demand and supply-side variables (e.g., supplier lead times, risk scores) that feed scenario analyses of centralization impacts on availability and pricing (Anthony et al., 2024).

For predictive maintenance and fleet-level forecasting, time-series models and supervised learning algorithms predict breakdown risks, remaining useful life (RUL), and maintenance windows, enabling schedule-aware dispatch and reduced downtime (Patil & Deshpande, 2025). Ensemble learning again plays a role in fusing sensor-based prognostics with operational logs to improve robustness across operating regimes.

Discrete-event simulation for operational validation

Predictions must be validated in operationally realistic environments prior to deployment. Discrete-event simulation (DES) is employed to model the temporal dynamics of logistics processes and mine operations. DES models the stochastic processes of vehicle arrivals, loading/unloading, travel times, and road deterioration effects. Meneses and Sepúlveda (2023) show how DES can capture productivity reduction and fuel consumption by explicitly modelling temporary road deterioration. DES-based validation enables the team to stress-test predictive recommendations under heavy-tailed disturbances and cascading delays, assessing resilience and service-level impacts.

The simulation layer interacts bidirectionally with the predictive modules. Predicted demand and maintenance schedules seed the simulation scenarios; in turn, simulation outcomes are used to retrain or recalibrate models when systemic biases or emergent behaviours are observed (a model-in-the-loop validation process).

Multi-objective evolutionary optimisation for scheduling and dispatch

For truck-shovel allocation and fleet dispatch in open-pit mines, multi-objective evolutionary algorithms (MOEAs) provide a natural fit. Alexandre et al. (2018) and Alexandre et al. (2019) demonstrate labeling-oriented nondominated sorting and evolutionary approaches tailored for many-objective optimisation problems. The scheduling problem is multi-objective by design: maximise throughput, minimise fuel consumption, minimise cycle time variance, and maintain equipment wear within safety limits. MOEAs explore trade-off fronts (Pareto-optimal sets) enabling planners to select solutions aligned with strategic preferences (e.g., sustainability vs production throughput).

Key design choices include representations (chromosome encodings of dispatch sequences and vehicle assignments), variation operators customized for dispatch problems (e.g., swap, insertion, and dedicated truck-shovel moves), and contextual feasibility checks (ensuring shovel availability windows and road-grade constraints). Ristovski et al. (2017) highlight the value of integrating optimisation with simulation to estimate robustness of candidate dispatch plans; this coupling is adopted here to ensure evaluated solutions perform under realistic stochasticity.

Connectivity and actuation considerations (6G, drones, and real-time routing)

Emerging communication paradigms enable novel actuation and coordination strategies. Sauvola et al. (6G in Logistics) theorize the role of ultra-low latency, high-throughput networks in enabling real-time supply-routing-delivery orchestration. Practically, this translates into finer time granularity in rerouting decisions, tighter coordination between centralized control and edge devices (vehicles, drones), and improved telemetry for predictive maintenance loops. For last-mile delivery, Shuaibu et al. (2025) comprehensively review strategies including drone integration which requires regulatory alignment, precise positioning (augmented by remote sensing geodata), and connectivity for command-and-control. The methodology prescribes modular actuation stacks where vehicles and drones act upon dispatch instructions that are continually updated by the ensemble predictive module and validated by simulation.

Evaluation metrics and validation procedures

Given the multidimensional objectives, evaluation adopts a portfolio of metrics: cost per delivered unit, fill-rate/availability (for pharmaceuticals), throughput (tons per hour for mines), fuel consumption per ton-km, schedule adherence, and robustness indicators (performance degradation under stress scenarios). Explainability and fairness metrics are also included for procurement and allocation decisions, ensuring that automated recommendations are interpretable to stakeholders (Anthony et al., 2024). Validation follows a staged pipeline: offline cross-validation of predictive modules, simulation-based stress testing, limited pilot deployments with human-in-the-loop oversight, and post-deployment monitoring with retraining triggers.

Results (Descriptive Analysis of Findings)

The results herein are descriptive, synthesising expected system behaviours and qualitative performance implications when the proposed methodology is applied, based on the evidence and examples from the referenced studies. Because the present article is an integrative synthesis rather than an empirical experiment, the "results" describe the predicted operational impacts and comparative advantages observed in cited works when analogous methods are employed.

Ensemble learning reduces forecasting error and stabilizes procurement decisions

Yaiprasert and Hidayanto (2024) provide empirical evidence that ensemble machine learning produces more accurate cost and demand forecasts than individual models in logistics contexts. Applying ensemble architectures in procurement forecasting decreases variance in cost predictions and yields more consistent parameter estimates for optimization models. The practical implication is a tighter procurement plan with lower safety stock requirements while maintaining service levels — an effect especially valuable for high-value, sensitive pharmaceutical supply chains (Anthony et al., 2024). In scenarios modelled by Anthony et al. (2024), improved forecasting underpins centralized procurement strategies that deliver lower per-unit prices while supporting higher availability, provided that the predictive system accounts for supply-side disruptions and geographical distribution constraints.

Centralization, predictive analytics, and systemic trade-offs

Anthony et al. (2024) examine the economic and clinical impacts of pharmaceutical supply chain centralization through AI-driven predictive analytics. Their comparative lessons from large-scale centralized procurement systems suggest that predictive analytics can mitigate some centralization risks by enabling proactive stock reallocation and dynamic ordering. However, centralization amplifies systemic exposure to forecasting errors; if forecasts underperform, availability in remote regions can decline rapidly. Therefore, predictive systems must embed uncertainty quantification and incorporate contingency buffers — design choices well supported by ensemble learning approaches that provide probabilistic outputs (Yaiprasert & Hidayanto, 2024). The descriptive outcome is a nuanced recommendation: centralization combined with robust predictive analytics improves average outcomes but requires explicit policies for extreme-event response and geographically differentiated risk management.

6G-enabled real-time logistics and last-mile flexibility

Real-time routing under 6G-like connectivity (Sauvola et al.) enables rapid reoptimization of delivery sequences in response to dynamic events (traffic jams, last-minute cancellations, or sudden demand spikes). When combined with drone-enabled last-mile legs (Shuaibu et al., 2025), urban deliveries can achieve lower latency and higher reliability for critical shipments (e.g., urgent medications). The descriptive analysis suggests that the coupling of high-bandwidth, low-latency networks with accurate geospatial urban/non-urban tagging (Ajani, 2018) creates operational envelopes where micro-optimization at the edge yields measurable gains in service levels and decreases in time-to-delivery for high-priority consignments.

Discrete-event simulation reveals operational sensitivities in mining fleets

Meneses and Sepúlveda (2023) describe how modeling temporary road deterioration within DES affects expected productivity and fuel consumption. Applying DES to truck-shovel operations demonstrates that small degradations in road quality propagate to substantial productivity declines and fuel cost increases. The descriptive implication is that predictive maintenance and routing strategies that preemptively address road deterioration (e.g., selective routing, speed recommendations, or road repair scheduling) can yield outsized returns. Moreover, integrating DES with MOEA-evaluated dispatch plans (Alexandre et al., 2018; Ristovski et al., 2017) reveals trade-offs between throughput and robustness — Pareto frontiers indicate that marginal throughput improvements often come at the expense of higher fuel usage and increased wear.

Multi-objective evolutionary algorithms balance throughput, cost, and sustainability

MOEAs applied to truck dispatch problems produce a spectrum of feasible operational policies that not only maximise throughput but also quantify the cost of achieving such gains in terms of fuel consumption and equipment wear (Alexandre et al., 2018; Alexandre et al., 2019). Decision-makers can select compromise solutions aligned with corporate sustainability targets. Descriptively, MOEAs make transparent the often hidden costs of aggressive production schedules and provide governance-ready artifacts (Pareto sets) that can be discussed across safety, finance, and operations stakeholders.

Predictive maintenance reduces downtime and enhances scheduling

Patil and Deshpande (2025) show that AI-enhanced fleet management and predictive maintenance reduce unexpected breakdowns, enabling more reliable scheduling and increasing effective fleet utilization. Integrating predictive maintenance outputs into MOEA-based dispatch reduces the frequency of schedule disruption, improving throughput consistency.

System-level synthesis: integrated gains and caveats

Synthesizing across domains, the integrative framework produces multiple mutually reinforcing benefits: reduced procurement cost and improved availability with centralized procurement informed by ensemble predictions (Anthony et al., 2024; Yaiprasert & Hidayanto, 2024); enhanced last-mile reliability through 6G-enabled routing and drone integration (Sauvola et al.; Shuaibu et al., 2025); and more efficient, robust truck-shovel dispatch through MOEA + DES coupling (Alexandre et al., 2018; Meneses & Sepúlveda, 2023). However, each gain is conditioned on careful validation, uncertainty handling, and human oversight to mitigate centralization risks and handle edge cases where AI predictions may be less reliable.

DISCUSSION

The preceding descriptive results point to deep implications for theory, practice, and future research. This discussion elaborates on interpretive threads, engages counter-arguments, surfaces limitations, and proposes future research directions.

Interpretive synthesis: modularity, explainability, and governance

A recurring lesson is the importance of modularity in system design. Each methodological component—ensemble learning, DES, MOEAs, connectivity modules, remote sensing inputs—should be modularized so that failures or model drift in one module do not cascade unchecked. Modularity facilitates validation, incremental upgrades, and human interpretability. Explainability matters for procurement and allocation decisions where stakeholders require justification for centralization policies or redistribution choices (Anthony et al., 2024). Ensemble architectures, while often complex, can be paired with model-agnostic explanation tools (e.g., SHAP or LIME-style reasoning) to provide interpretable insights into drivers of model outputs (Yaiprasert & Hidayanto, 2024). Governance protocols must specify acceptable risk thresholds for automated decisions and require human sign-off for decisions surpassing pre-defined criticality levels.

Counter-arguments and limitations

Several counter-arguments arise. First, the reliance on data-driven predictions can introduce overconfidence in contexts where data is sparse or non-stationary (e.g., sudden supply chain shocks). The ensemble approach partially mitigates this by reducing variance, but it cannot guarantee performance under distributional shift; therefore, stress testing via DES and conservative policymaking are essential (Meneses & Sepúlveda, 2023). Second, centralization benefits may be politically or institutionally infeasible in some jurisdictions due to procurement laws or supplier market structures; predictive models alone cannot solve regulatory or market constraints (Anthony et al., 2024). Third, the expected gains from 6G depend on infrastructure rollout, spectrum allocation, and cybersecurity protections; without secure connectivity, real-time routing introduces new attack surfaces and reliability concerns (Sauvola et al.). Finally, MOEA-generated Pareto solutions can overwhelm decision-makers if not properly visualised or constrained by practicable operational thresholds.

Ethical and social implications

AI-driven centralization and automation affect stakeholders unevenly. Centralized procurement can reduce prices but may displace local suppliers or increase dependencies on single vendors. Transparent evaluation of distributional impacts should be embedded in deployment pipelines to ensure equitable outcomes (Anthony et al., 2024). In mining operations, increased automation raises workforce transition questions; predictive maintenance reduces demand for reactive maintenance roles but increases demand for data-savvy operators and analysts. Policies should therefore include retraining and social transition plans.

Validation and safety: from simulation to real-world pilots

The path from simulation to deployment must be staged. DES provides an essential risk-mitigation step, allowing teams to observe emergent behaviours and verify that model recommendations do not produce unintended oscillations or systemic failure modes (Meneses & Sepúlveda, 2023). Pilot deployments should be geographically diverse to test generalisability and to surface edge-case behaviours (e.g., in non-urban settings identified via Ajani’s remote sensing approach). Post-deployment monitoring with retraining triggers ensures models remain calibrated; explainability logs support audits and stakeholder trust.

Future research directions

Several promising avenues emerge. First, research into robust ensemble methods that explicitly model distributional shift and provide calibrated uncertainty intervals would directly address centralization risk concerns. Second, tighter integration between MOEAs and online learning could enable adaptive dispatch that learns from operational outcomes in near-real-time while maintaining safety constraints. Third, studies that empirically evaluate the gains from 6G-like connectivity across varying infrastructural contexts will be critical for techno-economic feasibility assessment. Fourth, cross-disciplinary work on governance models that operationalise explainability requirements and human-in-the-loop supervisory protocols is needed to translate model outputs into accountable decisions. Finally, comparative case studies of centralized procurement under varying market structures would refine understanding of when centralization with AI is advantageous and when it is not (Anthony et al., 2024).

CONCLUSION

This article advanced an integrative framework for AI-driven optimisation across logistics and open-pit mining fleet operations. By combining ensemble machine learning for cost and demand forecasting, predictive analytics for centralized procurement assessment, remote sensing for geospatial fidelity, discrete-event simulation for operational validation, and multi-objective evolutionary optimisation for scheduling, the framework addresses key operational, economic, and sustainability objectives while foregrounding governance and validation. Descriptive synthesis of the literature suggests that ensemble approaches improve forecasting stability (Yaiprasert & Hidayanto, 2024), predictive analytics can make centralization more effective when uncertainty is properly managed (Anthony et al., 2024), 6G-like connectivity has transformative potential for real-time routing and last-mile delivery (Sauvola et al.; Shuaibu et al., 2025), and MOEA + DES coupling yields robust dispatch plans that expose trade-offs between throughput and sustainability (Alexandre et al., 2018; Meneses & Sepúlveda, 2023).

Practical implementation requires staged validation, transparent explainability mechanisms, modular system architecture, and policies that account for distributional impacts. Research should prioritise methods that enhance robustness to distributional shift, tighten optimisation-feedback loops, and empirically assess connectivity-enabled benefits in real-world deployments. Ultimately, the synthesis provided here aims to move the discourse beyond siloed method demonstrations toward an operationally coherent, ethically aware roadmap for deploying AI in high-stakes logistics and fleet operations.

REFERENCES

1. Yaiprasert C, Hidayanto AN. AI-powered ensemble machine learning to optimize cost strategies in logistics business. International Journal of Information Management Data Insights. 2024 Apr 1;4(1):100209.

2. Anthony OC, Oluwagbade E, Bakare A, Animasahun B. Evaluating the economic and clinical impacts of pharmaceutical supply chain centralization through AI-driven predictive analytics: comparative lessons from large-scale centralized procurement systems and implications for drug pricing, availability, and cardiovascular health outcomes in the U.S. Int J Res Publ Rev. 2024 Oct;5(10):5148-5161. Available from: https://ijrpr.com/uploads/V5ISSUE10/IJRPR34458.pdf

3. Sauvola J, Bräysy T, Myllymäki S, Lovén L, Bordallo M, Nguyen L, Nguyen T, Haapola JP, Hyysalo J. 6G in Logistics: Real-time supply-routing-delivery logistics.

4. Ajani OL. Extraction and validation of database of urban and non-urban points from remote sensing data. International Journal of Computer Applications Technology and Research. 2018;7(12):449-472.

5. Shuaibu AS, Mahmoud AS, Sheltami TR. A Review of Last-Mile Delivery Optimization: Strategies, Technologies, Drone Integration, and Future Trends. Drones. 2025 Feb 21;9(3):158.

6. Benlaajili S, F. Moutaouakkil A, Chebak H, Medromi L, Deshayes S, Mourad. Optimization of truck-shovel allocation problem in open-pit mines. In Smart Applications and Data Analysis: Third International Conference, SADASC 2020. 2020. pp. 243-255.

7. Patil AA, Deshpande S. AI-Enhanced Fleet Management and Predictive Maintenance for Autonomous Vehicles. International Journal of Data Science and Machine Learning. 2025;5(01):229-249.

8. Alexandre RF, Barbosa CHNR, Vasconcelos JA. LONSA: A labeling-oriented nondominated sorting

algorithm for evolutionary many-objective optimization. Swarm and Evolutionary Computation. 2018;38:275-286.

9. Ristovski K, Gupta C, Harada K, Tang HK. Dispatch with confidence: Integration of machine learning, optimization and simulation for open pit mines. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2017. pp. 1981-1989.

10. Zhang L, Xia X. An integer programming approach for truck-shovel dispatching problem in open-pit mines. Energy Procedia. 2015;75:1779-1784.

11. Meneses D, Sepúlveda FD. Modeling productivity reduction and fuel consumption in open-pit mining trucks by considering the temporary deterioration of mining roads through discrete-event simulation. Mining. 2023;3(1):96-105.

12. Awuah-Offei K, Brown O, Askari Nasab H. Improving truck-shovel energy efficiency through discrete event modeling. 2012.

13. Ben-Awuah E, Kalantari S, Pourrahimian Y, Askari-Nasab H. Hierarchical mine production scheduling using discrete-event simulation. International Journal of Mining and Mineral Engineering. 2010;2(2):137-158.

14. Alexandre RF, Campelo F, Vasconcelos JA. Multi-objective evolutionary algorithms for the truck dispatch problem in open-pit mining operations. Learning and Nonlinear Models. 2019;17(2):53-66.