

Article

A Safety-Constrained Multi-Objective Optimization Framework for Autonomous Mining Systems: Statistical Validation in Surface and Underground Environments

Rajesh Patil *  and Magnus Löfstrand 

School of Science and Technology (Mechanical Engineering, Digitalized Product and Production Development), Örebro University, SE-701 82 Örebro, Sweden

* Correspondence: rajesh.patil@oru.se

Abstract

The incorporation of artificial intelligence, multi-sensor perception, and cyber-physical control into mining operations offers tremendous opportunities for increasing productivity, safety, and sustainability. However, present frameworks focus on discrete subsystems rather than providing a unified, safety-constrained optimization method that has been verified in both surface and underground environments. This paper describes a scalable, hierarchical autonomous mining architecture that incorporates sensor fusion, edge intelligence, fleet coordination, and digital twin-based decision support. It is designed to operate in GNSS-denied conditions and extreme climatic constraints common to Nordic mining environments. A mathematical modeling approach formalizes vehicle dynamics, drilling mechanics, and multi-agent fleet coordination inside a safety-constrained multi-objective optimization formulation. The framework is validated using Monte Carlo simulation with uncertainty measurement, sensitivity analysis, and statistical hypothesis testing. The preliminary results show improvements over a typical baseline, with productivity increasing by approximately $24.3\% \pm 3.2\%$, energy consumption decreasing by $12.8\% \pm 2.5\%$, and safety risk decreasing by $48.6\% \pm 4.1\%$. A sensitivity study identifies localization accuracy, communication delay, and optimization weighting as the primary system performance drivers. The suggested framework serves as a reproducible and transferable reference model for next-generation intelligent mining systems, having direct applications to both industrial deployment and future research in autonomous resource extraction.

Keywords: autonomous mining systems; safety-constrained optimization; sensor fusion; Monte Carlo simulation; statistical validation; digital twin; multi-agent coordination



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1. Introduction

The mining industry is undergoing a fundamental transition, driven by the convergence of artificial intelligence (AI), advanced sensing technologies [1–4] and autonomous systems inside complex cyber-physical operational settings. Modern resource extraction is increasingly reliant on intelligent, data-driven ecosystems in which real-time perception, adaptive decision-making, and closed-loop control work together to maximize production efficiency, operational safety, and environmental sustainability. This transformation is driven by rising industrial pressures, such as diminishing ore grades, increased geological complexity, harsher environmental legislation, and increased safety requirements in hazardous and remote operating areas [5–10]. A major difficulty in both surface and underground mining is the inherent multi-objective conflict between productivity, safety, energy

consumption, and operational costs [11–15]. Increasing equipment utilization or haulage speed may boost throughput, but it also increases safety risk and energy demand. In contrast, severe regulatory limits, particularly in highly regulated nations, limit operational flexibility while ensuring worker safety and environmental compliance [16–18]. Managing these competing aims necessitates the creation of integrated optimization frameworks that can handle multidimensional system performance under uncertainty [19–26]. Recent advancements in autonomous mining technologies, such as GNSS-guided precision drilling, autonomous haulage systems (AHS), predictive maintenance platforms, and centralized fleet management, have resulted in quantifiable increases in operational efficiency and safety. However, the majority of present research focuses on application-specific solutions rather than system-level integration throughout the whole mining value chain. Critically, most existing techniques fail to explicitly account for the uncertainty caused by sensor noise, communication latency, equipment degradation, and changing environmental conditions—all of which are critical to real-world mining performance [27–33]. These restrictions are exacerbated in underground contexts by GNSS-denied localization conditions, geometrically limited drifts, heterogeneous rock mass characteristics, and strict ventilation and safety rules. Surface operations in Nordic regions confront additional problems due to sub-zero temperatures, poor visibility, and seasonal unpredictability, all of which have a substantial impact on system reliability [34–37]. Swedish mining companies, such as LKAB and Boliden, are leading examples of AI-driven automation at scale, using electrification, digitalized control systems, and autonomous equipment to boost output while maintaining high environmental and safety requirements. These activities provide a practical benchmark for understanding how autonomous mining systems can be deployed in highly regulated and climatically difficult regions, emphasizing the necessity for frameworks that are both technically rigorous and operationally grounded in Nordic conditions. Despite these developments, literature still lacks a cohesive framework that combines safety-constrained multi-objective optimization, uncertainty-aware decision-making, and system-level validation in both surface and underground mining contexts. Existing contributions address single subsystems or individual performance aspects, highlighting the crucial need for an integrated and statistically proven methodology. This work addresses the gap and therefore describes a safety-constrained multi-objective optimization framework for autonomous mining systems that operate in both surface and subsurface environments. The framework incorporates sensor fusion, edge intelligence, fleet coordination, and digital twin-based decision support into a hierarchical cyber-physical architecture. When tested under stochastic operational uncertainty, this unified strategy will result in statistically significant gains in productivity, energy efficiency, and safety risk compared to typical human-operated baseline systems. Validation involves Monte Carlo simulation, involves sensitivity analysis, and statistical hypothesis testing [38,39]. The paper is organized as follows. Related Research summarizes related studies and identifies the specific research gaps addressed. Section 2 discusses the suggested system architecture. Section 3 describes the mathematical modeling framework. Section 4 discusses the implementation strategy for surface and subsurface environments. Section 5 presents the simulation-based validation results together with a comprehensive statistical analysis. Section 6 analyzes operational performance and compares costs and benefits. Section 7 includes conclusions and recommendations for future research.

Related Research

Despite substantial progress, five fundamental gaps prevent the creation of fully integrated autonomous mining systems. First, existing research focuses on isolated subsystems, such as haulage, drilling, or underground LHD operations, rather than system-level integra-

tion across the entire mining value chain [1–5], resulting in limited interoperability among diverse equipment and control systems. Second, current AI-based techniques usually lack robustness in the face of unpredictable operational situations, such as GNSS-denied sub-surface environments, sub-zero temperatures, and changeable geological conditions [6,7]. These constraints are often viewed as external operational challenges rather than being incorporated directly into system design and optimization frameworks. Third, there is a large gap between real-time data fusion and edge-cloud orchestration, especially for latency-sensitive activities like collision avoidance and safety enforcement [11]. Existing centralized architectures are still sensitive to communication latency and scalability constraints at fleet scale. Fourth, while productivity and safety improvements have been observed, there is a scarcity of quantitative, cross-domain performance evaluation frameworks that systematically evaluate autonomous and conventional mining systems under similar and controlled conditions [15]. Fifth, human supervision needs, legal compliance limits, and safety-critical operational boundaries are rarely considered when designing autonomous systems, limiting their implementation in the most hazardous mining contexts [18,20]. To fill these deficiencies, this study introduces the unified safety-constrained multi-objective optimization framework described in Sections 2–4, and comprehensive statistical validation in Section 5. Each gap is directly addressed: system-level integration through the hierarchical cyber-physical architecture (Gap 1) [29]; uncertainty-aware design through stochastic simulation and robust control formulation (Gap 2) [32]; low-latency decision-making through distributed edge intelligence (Gap 3); quantitative cross-domain evaluation through the Monte Carlo validation framework (Gap 4) [38]; and safety-constrained optimization with explicit risk thresholds and regulatory alignment (Gap 5). Figure 1 shows a graphical representation of the autonomous mining optimization framework.

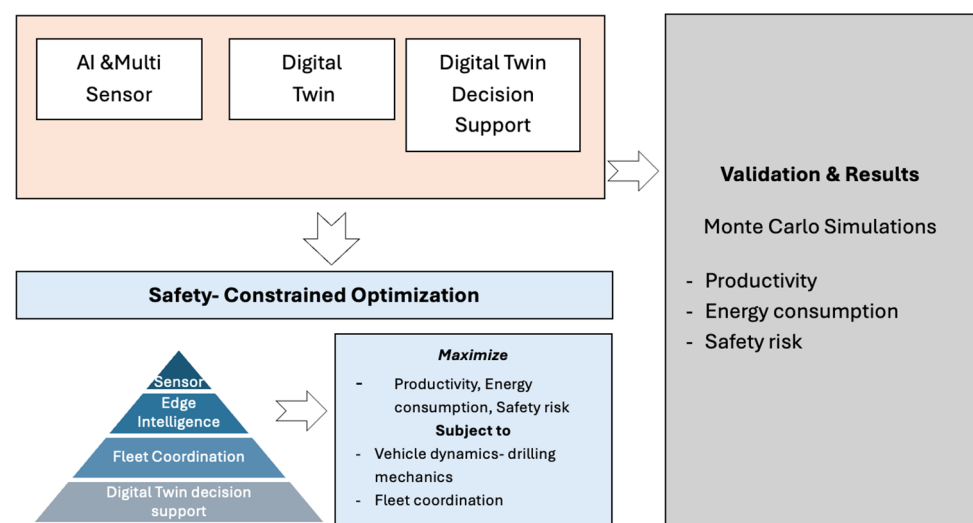


Figure 1. Graphical representation of the autonomous mining optimization framework.

2. A System Architecture for Autonomous Mining System

Autonomous mining systems are built with hierarchical, multi-layered cyber-physical architectures that combine sensing, communication, computation, and decision-making in both the surface and subsurface environments. These architectures provide incremental levels of autonomy, ranging from human supervision to totally autonomous execution, allowing for adaptive responses to changing geological, operational, and environmental conditions. The suggested architecture adheres to a cyber-physical systems paradigm, in which physical assets are tightly integrated with real-time digital intelligence to ensure optimal and safe operation. Unlike standard system descriptions, the proposed architec-

ture clearly includes uncertainty-aware perception, safety-constrained control, and multi-objective optimization, allowing for direct integration with the mathematical framework presented in Section 3. Figure 2 shows the system architecture and integration frameworks, while Section 2.8 details the real-time data flow and edge-cloud interaction.

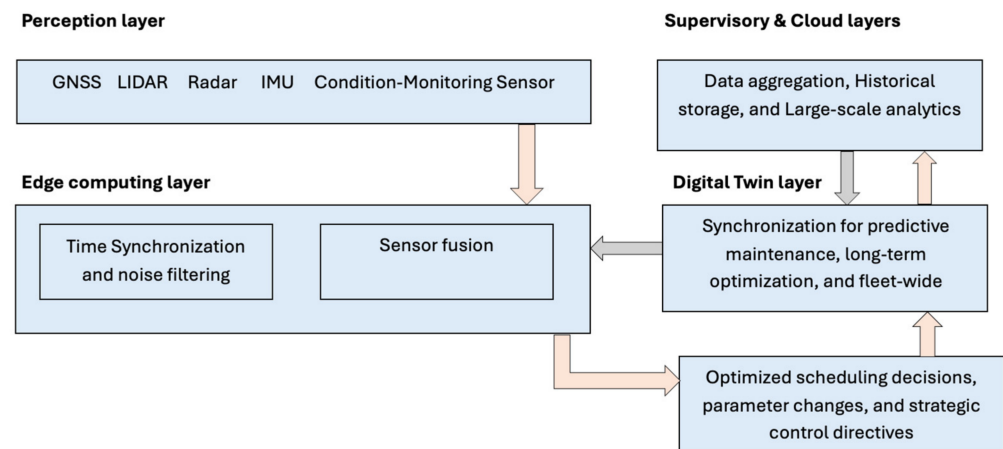


Figure 2. System architecture and integration frameworks.

2.1. Field and Perception Layer

The perception layer is made up of networked sensing systems that generate high-frequency operational and environmental data. Surface mining uses GNSS with real-time kinematic (RTK) correction for a positioning precision of $\pm 2\text{--}3$ cm. Underground or GNSS-denied areas use LiDAR-based SLAM and inertial navigation systems. Multi-modal sensing is used to ensure reliable perception in difficult settings. LiDAR enables three-dimensional terrain mapping, radar detects obstacles reliably even in dust and snow, and IMUs estimate vehicle motion. Additional sensors, such as vibration, temperature, pressure, and strain sensors, help to monitor equipment condition, while environmental sensors (e.g., PM2.5/PM10, gas detectors) ensure safety compliance. Sensor fusion is performed utilizing probabilistic frameworks, such as Bayesian estimation and filtering algorithms, which allow for robust state prediction in the face of ambiguity.

2.2. Edge Control and Communication Layer

Sensor data is handled at the edge-level controllers, allowing for latency-critical decisions. These controllers carry out tasks such as collision avoidance, adaptive speed control, trajectory tracking, and emergency shutdown. Control loops work at frequencies ranging from 10 to 100 Hz for navigation to 1 kHz for drilling equipment. Communication is enabled via industrial Ethernet, CAN-FD, and private 5G networks, which allow for end-to-end latency of less than 10–20 ms. Edge devices with GPUs or AI accelerators enable real-time inference, ensuring quick response to changing operating conditions. In Swedish mining operations, communication systems must withstand extreme cold (below -30 °C), electromagnetic interference, and complex terrain geometries. This requires redundant and fault-tolerant network design.

2.3. Supervisory Control and Fleet Management

At the supervisory level, centralized platforms manage fleet operations, production scheduling, and safety compliance. Fleet management systems dynamically allocate haulage routes, coordinate loading and dumping activities, and balance processing facility capacity. These systems typically manage fleets of 20–50 autonomous units, with planning horizons spanning from minutes to hours. Standardized communication protocols, such

as OPC UA and DDS, facilitate interoperability among different types of equipment and suppliers. This layer provides system-level coordination and acts as the foundation for the optimization and decision-making procedures outlined in Section 3.

2.4. Digital Twin and Decision Support Layer

Digital twin frameworks enable real-time synchronization of physical assets and virtual representations. Operational statuses are updated every 1–5 s, enabling predictive maintenance, energy optimization, and adaptive control schemes. Machine learning models use both historical and real-time data to estimate equipment degradation, optimize haulage cycles, and alter operational parameters. Furthermore, digital twins aid regulatory compliance by giving verifiable records of blasting accuracy, vibration restrictions, and environmental restraints.

2.5. Real-Time Data Communication and Edge Intelligence

Autonomous mining systems rely on high-bandwidth, low-latency communication networks, such as private LTE/5G, Wi-Fi 6, and fiber-optic infrastructure, to provide constant data transmission between mobile equipment and control centers. Edge intelligence provides localized decision-making in areas such as obstacle identification, path planning, and safety enforcement. This distributed architecture improves system resilience by minimizing reliance on centralized control while still ensuring operational continuation during communication outages. Centralized platforms combine data streams from numerous assets to provide predictive analytics, production forecasting, and system-wide optimization. Under degraded operating conditions, the design switches to a fault-tolerant mode to ensure safe operation. In the event of a communication failure, edge controllers operate in a decentralized fallback mode, performing local perception, collision avoidance, and trajectory control with onboard sensor fusion. When sensor degradation or failure is identified (for example, increasing covariance or signal loss), the system gracefully degrades by re-weighting remaining sensors, reducing operational speed, or stopping if safety criteria cannot be met. When connectivity is restored, supervisory control is resumed, and state synchronization with the central system is carried out to maintain consistency. This layered backup method ensures that vital functions continue to operate while maintaining safety in the face of uncertainty.

2.6. Architectural Implications of Mining Operations

The use of autonomous mining systems necessitates strict environmental, safety, and legal norms. System architectures must include climate-resistant hardware, GNSS-redundant localization, and strong cybersecurity frameworks. Redundancy, interoperability, and traceability are critical design elements that ensure dependable operation in adverse weather conditions and regulatory limits. These standards establish mining systems as benchmarks for autonomous operations in difficult, highly regulated situations.

2.7. Operating Classification Mining Stages

Autonomous mining systems are classified into several levels of autonomy, ranging from remote-controlled activities to totally unmanned mining environments. These levels show increased sensing, decision-making, and system independence while decreasing direct human interaction. Operations in advanced mining locations, are shifting toward supervised and fully autonomous systems, aided by AI-powered vision, real-time communication, and digital twin integration. This classification gives a context-based knowledge of deployment maturity for the suggested optimization framework. Table 1 shows the parameters of the autonomous mining system architecture.

Table 1. Parameters of the autonomous mining system architecture.

Architecture Layer	Component	Specification	Specific Considerations
Perception	GNSS (RTK)	$\pm 2\text{--}3$ cm positioning accuracy	Limited availability during polar night;
Perception	LiDAR	16–64 channels, 120–250 m range	Performance degradation due to snow/ice contamination
Perception	Radar	76–81 GHz, all-weather operation	Preferred sensing modality in snowfall and fog
Perception	IMU	$<0.01^\circ/\text{s}$ angular rate resolution	Thermal drift at sub-zero temperatures
Condition Monitoring	Vibration sensors	5–20 kHz sampling rate	Cold-rated sensor housings required
Communication	Industrial Ethernet	1–10 Gbps	Hardened cabling for -30°C environments
Communication	Private 5G	<20 ms latency	Coverage challenges in remote arctic regions
Edge Control	Control loop frequency	10–100 Hz (navigation), up to 1 kHz (drilling)	Increased fault tolerance required
Fleet Management	Fleet size	20–50+ autonomous units	Seasonal production variability
Digital Twin	Update rate	1–5 s	Used for regulatory reporting and compliance

2.8. Real-Time Data Flow and Edge–Cloud Interaction Mechanism

To clarify the operational logic of the proposed architecture (Figure 1), the data interaction across layers is explicitly stated as a closed-loop, multi-stage processing pipeline. Raw sensor data from the perception layer, which includes GNSS, LiDAR, radar, IMU, and Condition-Monitoring sensors, is collected at high sampling rates (100–500 Hz) and then subjected to time synchronization and noise filtering at the edge computing layer. Sensor fusion is performed using probabilistic estimation frameworks (e.g., extended Kalman filtering or factor graph optimization), producing a consistent and real-time estimate of the system state $\hat{x}_k$ including position, velocity, orientation, and system health indicators. Edge controllers exploit this fused state instantaneously to perform latency-critical control activities like collision avoidance, trajectory tracking, adaptive speed regulation, and emergency braking under millisecond response time limits. These local judgments are independent of cloud connectivity and assure safety in communication-disrupted or GNSS-denied conditions. The supervisory and cloud layers receive compressed and structured data streams, such as status estimations, event logs, and performance metrics, via

low-latency communication networks (e.g., private 5G, industrial Ethernet). At this level, data aggregation, historical storage, and large-scale analytics are carried out. Digital twin models continuously synchronize with field data at 1–5 s intervals, allowing for predictive maintenance, long-term optimization, and fleet-wide coordination. The cloud layer generates optimized scheduling decisions, parameter changes, and strategic control directives, which are then transmitted back into the edge layer. These updates improve local control rules, resulting in a hierarchical feedback loop that combines real-time responsiveness and long-term system optimization. This edge-cloud co-processing paradigm enables scalability, reliability, and efficient operation while adhering to the strict environmental and legal constraints of autonomous mining systems.

3. Mathematical Modeling: Autonomous Mining Systems

The integrated autonomous mining system is designed as a multi-agent cyber-physical system that operates in both surface and underground environments. Autonomous assets (transport trucks, LHDs, drill rigs, and bolters) interact with dynamic geological, infrastructure, and regulatory restrictions. The system is described in discrete time as a nonlinear stochastic state-space system.

$$x_i(k+1) = f_i(x_i(k), u_i(k), w_i(k)) \quad (1)$$

$$y_i(k) = h_i(x_i(k), v_i(k)) \quad (2)$$

3.1. Sensor Fusion and Localization Model

Environmental perception and vehicle localization in autonomous mining systems are modeled as a nonlinear state estimation problem with asynchronous and noisy measurements from heterogeneous sensors. The system state is defined as

$$x_k = [p_k v_k \theta_k b_k]^\top \quad (3)$$

The state propagation follows a nonlinear motion model:

$$x_k = f(x_{k-1}, u_k) + w_k \quad (4)$$

Sensor readings across multiple modalities $j \in \{1, \dots, N\}$ are given by:

$$z_{j,k} = h_j(x_k) + v_{j,k} \quad (5)$$

The optimal state estimate is produced using weighted nonlinear least-squares optimization (similar to EKF/factor graph formulation):

$$\hat{X}_k = \underset{X_k}{\operatorname{argmin}} \sum_{j=1}^N \|z_{j,k} - h_j(X_k x_k)\|_{\Sigma_j}^2 \quad (6)$$

where $\|e\|_{\Sigma}^2 = e^\top \Sigma^{-1} e$.

In underground situations with GNSS denial, LiDAR-inertial odometry and radar limitations, given as relative pose factors, improve localization robustness.

$$r_{i,k} = x_k \ominus X_{k-1} - \Delta x_{i,k} \quad (7)$$

This allows for seamless localization across surface (GNSS-based) and subsurface (LiDAR-inertial) settings.

i. Adaptive Localization Switching and Reliability Assessment

To achieve reliable localization across diverse mining conditions, the proposed framework includes an adaptive sensor-selection and reliability-based switching mechanism that dynamically switches between GNSS-enabled surface positioning and GNSS-denied subsurface localization.

a. Positioning Source Reliability Estimation

At each time step k , the system evaluates the reliability of each location source (GNSS, LiDAR-SLAM, IMU) using a confidence metric generated from measurement covariance and signal quality indicators. The sensor reliability score (j) is defined as:

$$\rho_j^{(k)} = \frac{1}{\text{trace}(\Sigma_j(k)) + \eta_j^{(k)}} \quad (8)$$

where $\Sigma_j(k)$ represents the measurement covariance matrix $\eta_j^{(k)}$ which includes sensor-specific degradation factors, such as:

- GNSS signal-to-noise ratio (SNR) satellite visibility.
- LiDAR feature density and scan-matching residual error.
- IMU drift and bias instability.

A normalized confidence weight $w_j(k)$ is then assigned.

$$w_j(k) = \frac{\rho_j^{(k)}}{\sum_{j=1}^N \rho_j^{(k)}} \quad (9)$$

This formulation assures that more reliable sensors contribute more significantly to the fused state estimation.

b. GNSS-to-Underground Transition (Wellhead Switching)

At transition zones such as mine entrances (wellhead regions), GNSS signal deterioration is detected by:

- Drop in satellite count (<4 satellites).
- Increase in dilution of precision (DOP).
- Rapid growth in GNSS covariance (Σ_{GNSS}).

When the GNSS confidence weight $w_{\text{GNSS}}(K)$ falls below a predefined threshold δ_{GNSS} , the system gradually reduces its effect in the fusion process.

$$w_{\text{GNSS}}(k) \rightarrow 0$$

Simultaneously, LiDAR-SLAM and IMU-based odometry are activated as primary localization sources. The transition is smooth and continuous, avoiding abrupt switching by allowing overlapping sensor contributions during the boundary phase.

c. GNSS-Denied Localization Using LiDAR-IMU Fusion

In subsurface situations, localization is maintained through tightly coupled LiDAR-IMU fusion. The IMU enables high-frequency motion prediction,

$$\bar{x}_k = f(x_{k-1}, u_k) + \omega_k, \quad (10)$$

while LiDAR scan matching provides correction updates based on geometric feature alignment:

$$Z_{\text{LiDAR},k} = h_{\text{LiDAR}}(x_k) + \omega_k \quad (11)$$

The combined state estimate is obtained using nonlinear optimization (e.g., factor graph or EKF) minimizing drift accumulation:

$$\hat{x}_k = \operatorname{argmin}(\|x_k - \bar{x}_k\|_Q^2 + \|z_{LiDAR,k} - h_{(x_k)}\|_{R^{-1}}^2) \quad (12)$$

Loop closure detection and map-based correction are periodically applied to reduce long-term drift, which is critical for extended underground operations.

d. Re-Localization during the underground-to-surface transition

When returning to the surface, GNSS signals are reintroduced into the fusion framework. A consistency check is performed between the LiDAR-IMU predicted position and GNSS readings.

$$\|x_{GNSS} - x_{LiDAR-IMU}\| < \epsilon_{relocalization}$$

If the discrepancy is within acceptable limits, GNSS weights are gradually increased, restoring it as the primary positioning source. If not, a correction step is used to prevent localization jumps, such as map alignment or delayed GNSS integration.

3.2. Multi-Agent Fleet Coordination and Optimization

Fleet-level coordination is defined as a limited optimization problem that seeks to improve production while minimizing energy consumption and safety risk. Fleet coordination is defined as a multi-objective optimization problem.

$$\min_u J_f = \sum_{i=1}^M (\alpha T_i + \beta E_i + \gamma R_i) \quad (13)$$

In Equation (8), the weighting factors α , β , and γ indicate the relative importance of productivity, energy efficiency, and safety risk. These values are not constants. Instead, they are dynamically allotted based on operational priorities, regulatory constraints, and environmental factors. In production-driven contexts (e.g., high-demand surface haulage), productivity is prioritized ($\alpha \uparrow$), while safety-critical underground environments prioritize safety ($\gamma \uparrow$) to enforce stricter risk limitations. Weights are normalized so that $\alpha + \beta + \gamma = 1$ enables balanced optimization.

In practice, weight selection is guided by (i) rule-based policies derived from operational guidelines, (ii) sensitivity analysis to assess system reaction to parameter variation, and (iii) offline calibration using historical or simulated datasets. Additionally, adaptive tuning can be implemented through higher-level supervisory control or learning-based approaches (e.g., reinforcement learning), which allow for dynamic weight modification in response to real-time system states such as increasing collision probability or energy constraints, where the individual cost components are defined as:

$$T_i = \int_0^{T_h} (\tau_i(t) + \delta_i(t)) dt$$

$$E_i = \int_0^{T_h} P_i(t) dt$$

$$R_i = \int_0^{T_h} (P_{\text{collision},i}(t) + P_{\text{failure},i}(t)) dt$$

Subject to:

$$x_i(k+1) = f_i(x_i(k), u_i(k)) + w_i(k) \quad (14)$$

$$x_i(k) \in \mathcal{X}_{\text{safe}}, u_i(k) \in \mathcal{U}_{\text{limits}} \quad (15)$$

Task allocation Constraints:

$$\sum_{i=1}^M \delta_{ij} = 1, \delta_{ij} \in \{0, 1\} \quad (16)$$

3.3. Drilling Dynamics and Rock Interaction Model

Drilling is an important technology for efficient resource extraction, as evidenced by studies on penetration enhancement in hot dry rock, drag reduction in shale drilling, and fracture evaluation using pressure transient analysis. For autonomous drilling operations, the penetration dynamics can be modeled by combining rock-bit interaction mechanics, axial force balancing, and rotational cutting resistance. ROP is calculated as a function of thrust force, torque, rock characteristics, and control inputs. Drilling dynamics are modeled using force-torque and energy-based formulas. The drilling model calculates rock compressive strength (σ_c) using a hybrid approach that combines prior geological data and real-time estimation. Initially, σ_c is determined using pre-drilling geological surveys and historical rock property databases. During operation, it is constantly updated with real-time drilling feedback obtained via rate of penetration (ROP), torque, and thrust measurements. An inverse estimating approach is utilized to dynamically change σ_c based on the differences between predicted and observed ROP. This allows the system to account for geographic variation in rock characteristics while maintaining adaptive, accurate drilling control under changing geological conditions.

i. Axial Force and Penetration Rate

The axial penetration dynamics are determined by:

$$\dot{z}(t) = ROP = \frac{\eta p}{A_b} (F_t - F_r) \quad (17)$$

ii. Rock Resistance Force

The rock resistance is represented using compressive strength and bit-rock contact.

$$F_r = \sigma_c A_b + k_r \dot{z}(t) \quad (18)$$

iii. Rotational Cutting Torque

The drilling torque necessary for autonomous control is expressed as follows:

$$T = \mu_c F_t r_b + J_b \dot{\omega} \quad (19)$$

iv. Coupled Energy-Based Penetration Model

The mechanical specific energy (MSE), often used for autonomous optimization, is defined as:

$$MSE = \frac{F_t}{A_b} + \frac{2\pi T_n}{A_b \dot{z}} \quad (20)$$

v. Autonomous Control Law

A closed-loop adaptive thrust–torque control method is defined as:

$$F_t(t+1) = F_t(t) + K_p(ROP_{ref} - \dot{z}(t)) + K_i \int e(t) dt \quad (21)$$

3.4. Safety and Reliability Modeling

The operational reliability of autonomous mining systems is analyzed using stochastic failure theory, which assumes that crucial subsystems (sensing, actuation, communication, and control) fail without leaving any memory. The system reliability function can be stated as

$$R(t) = \exp(-\lambda t) \quad (22)$$

The failure rate accounts for both hardware-related degradation (e.g., sensors, actuators, power electronics) and software-induced problems (e.g., perception mistakes or control instability). For complicated autonomous mining systems, the entire failure rate can be broken down as

$$\lambda = \sum_{i=1}^M \lambda_i \quad (23)$$

This approach allows for a quantitative comparison of the reliability of conventional and autonomous operations under various environmental conditions. Safety enforcement is carried out using a risk-constrained decision-making framework that combines deterministic rule-based restrictions and probabilistic safety assessments. The probability of unsafe events, such as crashes or loss of control, is limited by an allowable safety threshold (ε_{safe}), defined as

$$P_{collision} \leq \varepsilon_{safe} \quad (24)$$

where $P_{collision}$ is estimated by applying Bayesian inference or Monte Carlo sampling to expected vehicle trajectories and obstacle states. The collision probability is calculated as:

$$P_{collision} = \int X_{unsafe} p(x_k | z_{1:k}) dx_k \quad (25)$$

with $\mathcal{X}_{unsafe}$ representing the unsafe state space and $p(x_k | z_{1:k})$ denoting the posterior state distribution determined from sensor fusion.

To provide operational resilience, control actions u_k are determined by solving a restricted optimization problem.

$$\min_{u_k} J(x_k, u_k) \text{ subject to } P_{collision}(u_k) \leq \varepsilon_{safe} \quad (26)$$

where $J(\cdot)$ is a performance cost function that measures productivity, energy consumption, and mission completion time. This formulation ensures that autonomous judgments adhere to set safety margins while retaining high operational efficiency. Overall, the proposed safety and reliability model allows for a quantitative assessment of autonomous mining system dependability while also providing a mathematically rigorous framework for certifying autonomous operations in accordance with strict mining safety requirements.

To ensure analytical tractability, the reliability formulation presupposes statistical independence amongst subsystem failures (sensing, communication, actuation, and control). While this assumption makes modeling easier, it may not capture all common-cause failures or interdependencies (for example, power outages affecting many subsystems). In practice, partial reliance can be incorporated via aggregated failure rates or conditional probability adjustments based on empirical data. Future extensions will look into dependency-aware models (such copula-based or system-theoretic techniques) to better reflect correlated failures in tightly connected cyber-physical systems.

3.5. Integrated System Objective Function

The autonomous mining system is defined as a limited multi-objective optimization problem that maximizes productivity while minimizing safety risk [40], operating costs, and energy consumption over a finite planning horizon.

The integrated system objective function is defined as:

$$J = \sum_{k=0}^N (\omega_1 Q(k) - \omega_2 C(k) - \omega_3 S(k) - \omega_4 E_m(k)) \quad (27)$$

i. Productivity and Cost Modeling

Productivity is expressed as a function of task completion rate and equipment utilization:

$$Q(k) = \eta_u(k)\dot{M}(k) \quad (28)$$

Operational cost is modeled as

$$C(k) = C_f(k) + C_m(k) + C_l(k) \quad (29)$$

ii. Safety Risk Function

Safety performance is quantified using probabilistic risk metrics:

$$S(k) = P_{\text{collision}}(k) + P_{\text{failure}}(k) \quad (30)$$

with

$$P_{\text{failure}}(k) = 1 - e^{-\lambda\Delta t} \quad (31)$$

where λ is the system failure rate and Δt is the control interval. Safety constraints enforce acceptable risk levels:

$$P_{\text{collision}}(k) \leq \varepsilon_{\text{safe}}, P_{\text{failure}}(k) \leq \varepsilon_{\text{safe}} \quad (32)$$

iii. Energy and Sustainability Modeling

Energy consumption for haulage and drilling operations is modeled as

$$E_m(k) = \int_{t_k}^{t_{k+1}} F_h(t)v(t)dt \quad (33)$$

where F_h is the required traction or drilling force and v is the equipment velocity or penetration rate. For battery-electric equipment, emission equivalents are estimated as

$$E_{\text{CO}_2}(k) = \alpha E_m(k) \quad (34)$$

where α is the grid-dependent emission factor, relevant for sustainability assessment in Nordic mining operations.

iv. System Constraints

The optimization is subject to dynamic and operational constraints:

$$x_{k+1} = f(x_k, u_k) + w_k \quad (35)$$

$$u_{\min} \leq u_k \leq u_{\max} \quad (36)$$

$$x_k \notin \mathcal{X}_{\text{unsafe}} \quad (37)$$

where x_k and u_k denote system states and control inputs, respectively, and $\mathcal{X}_{\text{unsafe}}$ represents forbidden safety states.

4. Autonomous Mining System Implementation

Autonomous mining systems are implemented as integrated cyber-physical frameworks that combine vision, edge intelligence, and supervisory control to allow for safe and efficient operations in both surface and underground environments. While surface mining benefits from GNSS-based localization and open operational spaces, underground conditions necessitate GNSS-independent navigation, robust sensing, and stringent safety regulations. The suggested implementation shows how the multi-objective optimization and safety-constrained control framework described in Section 3 may be applied to major mining operations to improve productivity, safety, and energy efficiency in uncertain situations.

4.1. Surface Mining Systems

Autonomous surface mining operations incorporate haulage, drilling, and material management into a unified digital framework. Autonomous excavators and haul trucks use GNSS/RTK positioning in conjunction with LiDAR, radar, and vision sensors to provide real-time localization and obstacle recognition in tough environments such as dust, snow, and low visibility. AI-powered fleet management solutions dynamically optimize routing, dispatching, and cycle times, and drive-by-wire control allows for adaptive speed and trajectory planning. Autonomous drilling and blasting systems use high-precision positioning and sensor-based data to control penetration rate, thrust, and torque, resulting in consistent blast hole quality and better fragmentation outcomes. Material handling systems connect loading zones, stockpiles, and processing plants via synchronized data transmission, allowing for continuous and balanced material movement. These surface subsystems are modeled using the multi-objective optimization framework described in Section 3, which optimizes productivity, energy consumption, and safety risk simultaneously. The findings reported in show considerable gains in haulage efficiency, lower energy usage, and improved operating safety when compared to conventional systems. The suggested implementation of an Autonomous Mining System (AMS) for surface environments, as shown in Figure 3, is built on a tightly integrated cyber-physical architecture that connects autonomous loading, hauling, processing, and fleet-level optimization.

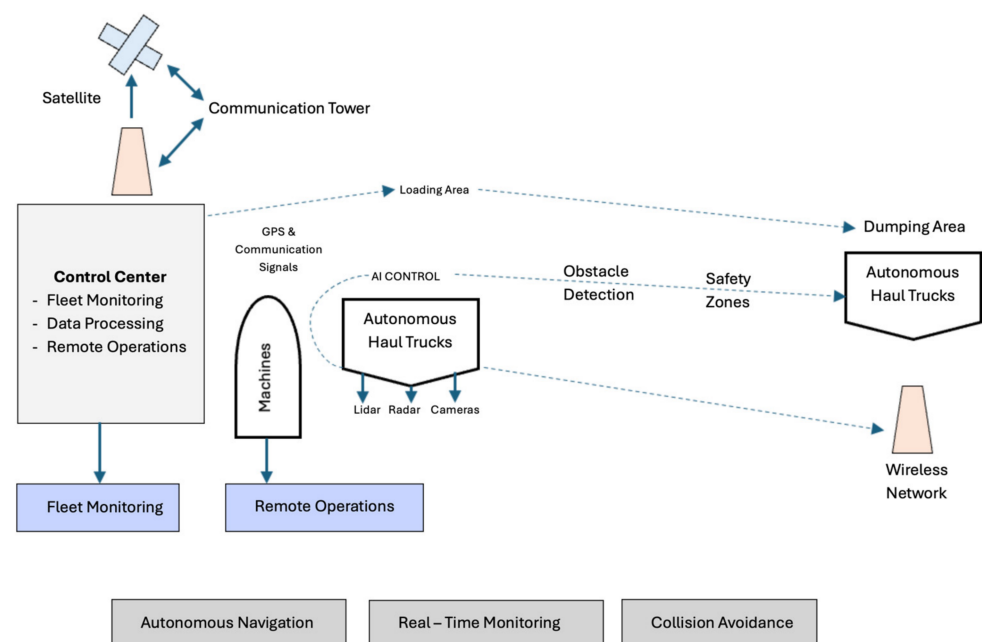


Figure 3. Haulage system in surface mining.

4.2. Underground Mining Systems

Underground autonomous mining systems work in GNSS-denied, geometrically limited, and safety-critical conditions that necessitate sophisticated vision, localization, and control algorithms. Autonomous drilling systems use LiDAR-based SLAM, inertial navigation, and machine vision to accomplish precise drill location and adaptive parameter control. Real-time sensor data allows for dynamic adjustment of drilling settings based on rock mass attributes, resulting in improved fragmentation and reduced operational variability. Figure 4 shows autonomous drilling and blasting systems in surface mining.

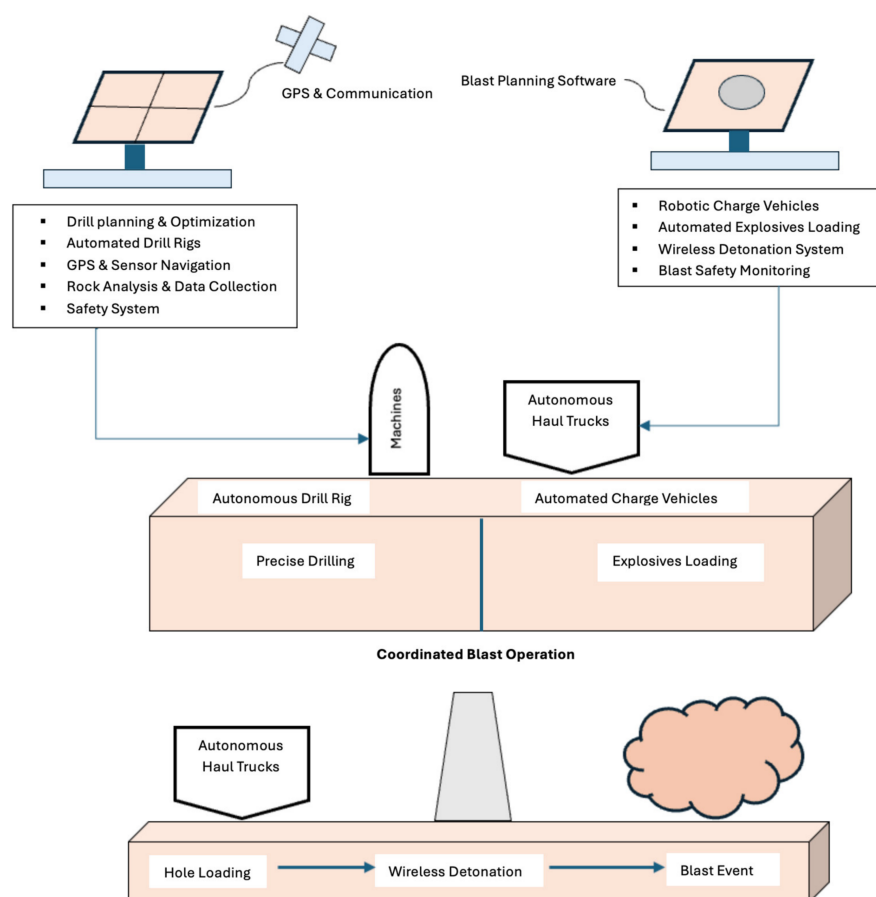


Figure 4. Drilling and blasting systems in surface mining.

Autonomous load-haul-dump (LHD) systems use multi-sensor fusion and continuously updated digital mine maps to load, haul, and dump. Edge-based control allows for real-time obstacle recognition and path replanning, while centralized fleet coordination reduces congestion and optimizes resource use. Ground support and inspection systems use autonomous bolters, inspection robots, and sensor networks to monitor geotechnical stability and detect hazards including rock deformation and gas accumulation. Figure 5 shows autonomous load-haul-dump systems.

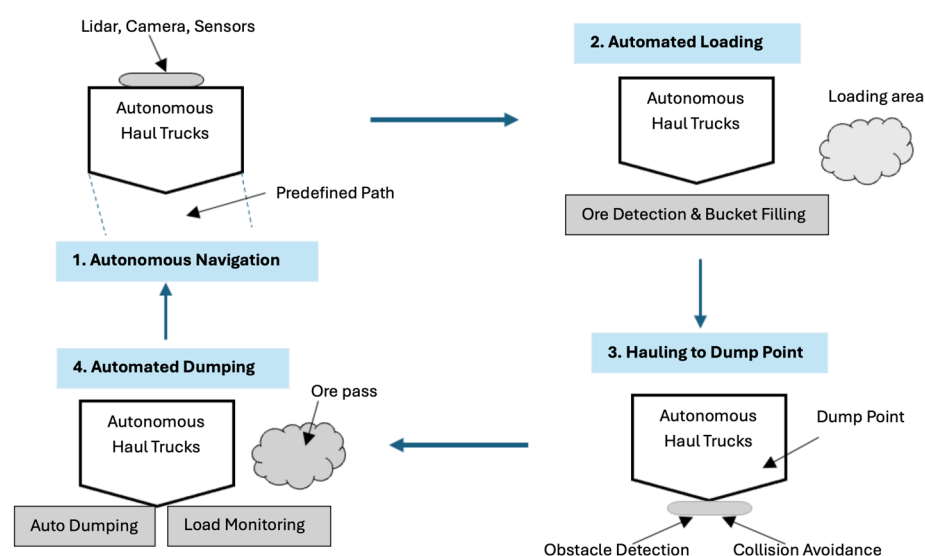


Figure 5. Autonomous load-haul-dump systems.

The proposed system uses safety-constrained optimization and probabilistic risk modeling to keep autonomous judgments within acceptable safety boundaries. The combination of digital twins with real-time data analytics facilitates predictive maintenance and adaptive operational control. The proposed results are confirmed that the suggested approach greatly decreases safety hazards and enhances operational robustness in underground environments.

5. Simulation-Based Validation

This section describes the entire simulation-based validation architecture designed to evaluate the proposed autonomous mining system. The methodology is intended to assure reproducibility, statistical rigor, and direct comparability of the autonomous and traditional baseline systems under similar operating conditions. Statistical significance testing, uncertainty quantification, Monte Carlo robustness evaluation, and sensitivity analysis are all provided in separate subsections.

5.1. Simulation Framework and Baseline Definition

The validation framework is based on a controlled comparison of two well-defined scenarios: a traditional baseline system representing standard human-operated mining operations, and the proposed autonomous system, which includes sensor-fusion localization, edge-control architecture, and AI-driven fleet coordination. The typical baseline is parameterized to reflect industry-standard manual activities, such as operator-driven dispatching, reactive maintenance strategies, manual haulage cycle control, and traditional drill-and-blast processes that do not automatically adjust parameters. The baseline performance figures are based on established industry benchmarks and operational data provided in the literature for Swedish underground and surface mining environments [8,15]. Both systems are evaluated under identical operational constraints: haul truck payloads of 200–400 t, underground LHD payloads of 10–18 t, a drilling thrust of 20–35 kN, a rotation speed of 150–300 rpm, penetration rates of 5–15 mm s^{−1}, drift widths of 4–6 m, a communication latency of 50–100 ms, and ambient temperatures as low as −30 °C. Multi-modal sensor inputs—GNSS, LiDAR, radar, IMU, and odometry—are modeled with sample rates of 100–500 Hz, providing the foundation for dynamic state estimation and control. The safety threshold is fixed at $\epsilon_{\text{sa oe}} = 0.05$ (collision probability limit) for all runs. Table 2 summarizes the full simulation parameter space. The baseline system depicts a traditional human-operated mining operation, complete with manual dispatching, operator-dependent haulage cycles, fixed-parameter drilling, and reactive maintenance techniques. The baseline performance characteristics are determined from a combination of published industry benchmarks, reported operational ranges, and confirmed simulation assumptions for Nordic mining conditions. To ensure comparability between situations, key characteristics such as payload capacity, cycle duration, energy consumption, and failure rates are picked from literature ranges and normalized. To provide transparency, Tables 2 and 3 explicitly identify all simulation inputs, and both baseline and autonomous scenarios are subject to the same environmental and operational limitations. This regulated arrangement allows for direct attribution of performance variations to the suggested autonomous framework rather than environmental variability.

Table 2. Simulation parameter space for the validation framework.

Parameter	Range	Description
Haul truck payload	200–400 t	Surface AHS operations
LHD payload	10–18 t	Underground operations
Drift width	4–6 m	Underground mining geometry
Drilling thrust	20–35 kN	Electrohydraulic drill rigs
Rotation speed	150–300 rpm	Drilling systems
Penetration rate	5–15 mm/s	Rock UCS 80–300 MPa
Sensor fusion rate	100–500 Hz	LiDAR, IMU, GNSS combined
Position accuracy (drill)	±5–10 mm	Drill collar localisation
Position accuracy (vehicle)	±10–20 cm	LHD/truck navigation
Communication latency	50–100 ms	Edge-to-fleet systems
Ambient temperature	Down to −30 °C	Arctic conditions
Safety threshold (ϵ_{safe})	0.05	Maximum collision probability
GNSS availability	60–80%	Surface variability
LHD cycle time	20–35 min	Nominal underground cycle
Energy per cycle	15–25 kWh	Electric equipment baseline

Table 3. Key performance indicator comparison—autonomous vs. baseline.

KPI	Baseline System	Autonomous System	Change
Equipment utilization	65–75%	85–95%	+20–30%
Cycle time variance	High variability	Reduced by 10–20%	Improved
Energy consumption	Baseline	Optimized	−10–15%
Safety exposure	High (human factor)	AI-controlled	−40–60%
System reliability $R(t)$	Lower	>0.95 over 30 days	Significantly higher
Material throughput	Baseline capacity	>350,000 t/day	Increased

5.2. Key Performance Indicators

System performance is measured using four key quantitative indicators: productivity (Q), energy consumption (E), safety risk (S), and operational cost (C). Productivity is defined as material throughput and equipment utilization efficiency. Energy consumption measures the operating efficiency of haulage and drilling cycles. Safety is measured probabilistically utilizing collision and failure probabilities obtained from system state distributions. The cost includes fuel, maintenance, and labor. These four variables work together to provide a holistic assessment that includes operational, economic, and safety dimensions. Table 3 shows the simulation study's key performance indicator (KPI) results, with mean values compared across both scenarios.

5.3. Statistical Validation Results

Monte Carlo simulations were performed with separate runs per scenario, accounting for random perturbations in localization error, communication delay, environmental visibility, geological variability, and subsystem failure rates. Each KPI was assigned a mean performance value, standard deviation, and 95% confidence interval (CI). Statistical significance was determined with paired *t*-tests for normally distributed measures and Wilcoxon signed-rank tests for non-normal distributions at a *p*-value of <0.05. The autonomous system provides statistically significant gains in all three key performance dimensions:

i. *Productivity*: $\Delta Q = +24.3\% \pm 3.2\%$ (95% CI), indicating persistent gains in material handling efficiency due to continuous 24/7 operation, elimination of shift-change delays, and AI-driven dispatching [40–48]. Figure 6 depicts the productivity distribution over simulated runs with confidence bounds.

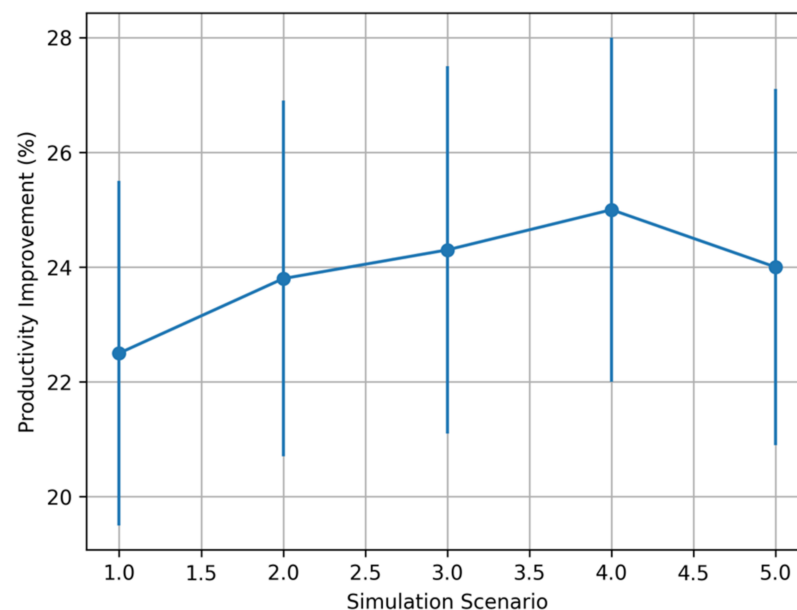


Figure 6. Increased productivity across simulation situations with a 95% confidence interval.

ii. *Energy consumption*: $\Delta E = -12.8\% \pm 2.5\%$ (95% CI), accomplished by optimized routing, adaptive speed control, and predictive load management. Figure 7 depicts the energy distribution under both situations.

iii. *Safety risk*: $\Delta S = -48.6\% \pm 4.1\%$ (95% CI), indicating a significant reduction in collision and subsystem failure exposure. Figure 8 depicts the impact of communication latency on safety performance inside an autonomous framework.

Two-sample *t*-tests across all KPIs yielded $p < 0.01$, indicating that the observed improvements are due to the proposed optimization and control system, not stochastic variation. Table 4 displays the entire statistical results. A convergence analysis was performed to ensure that the Monte Carlo sample size was enough. The findings show that important performance measures, such as the observed 24.3% productivity increase, stabilize after around 350–400 iterations, with variability in mean values falling below 1%. The iterations ensure statistical convergence and reduce the impact of random perturbations on reported results. The observed benefits (e.g., a 48.6% reduction in safety risk) were achieved under controlled simulation circumstances with certain assumptions about system setup, environmental variability, and parameter ranges. These findings should be taken as relative performance improvements within the studied settings, rather than as universally applicable outcomes. Actual performance may differ depending on site-specific variables such as geological conditions, operational procedures, and system maturity.

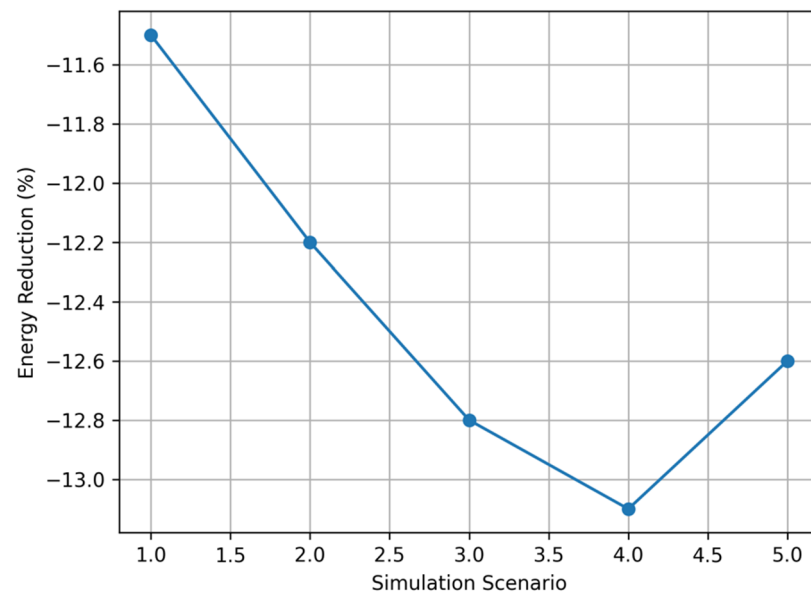


Figure 7. Autonomous optimization framework reduces energy use.

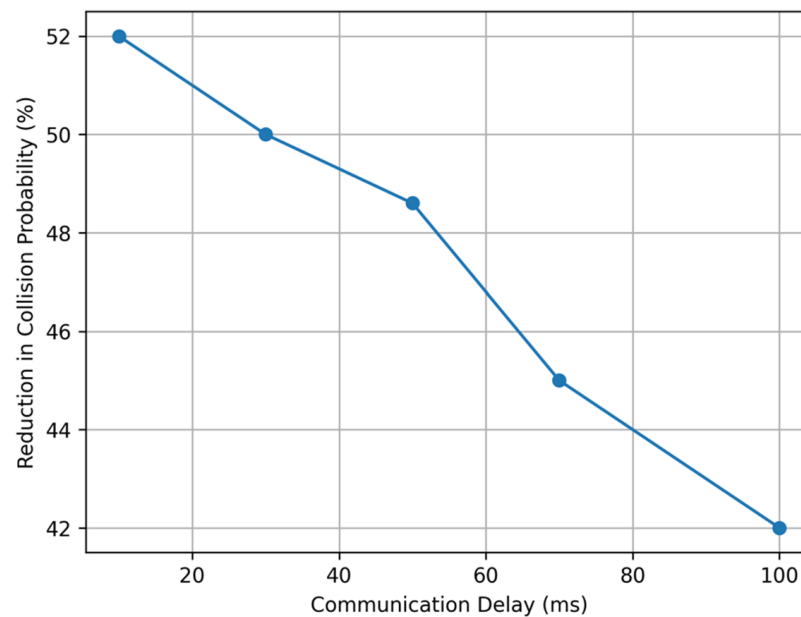


Figure 8. Effect of communication delays on safety performance.

Table 4. Statistical validation results.

Metric	Baseline Mean	Autonomous Mean	Change	95% CI	<i>p</i> -Value
Productivity (Q)	Normalized = 1.0	1.243	+24.3%	±3.2%	<0.01
Energy consumption (E)	Normalized = 1.0	0.872	−12.8%	±2.5%	<0.01
Safety risk (S)	Normalized = 1.0	0.514	−48.6%	±4.1%	<0.01

5.4. Sensitivity Analysis

A sensitivity study was carried out to determine the impact of major system factors on overall performance. Both one-at-a-time (OAT) and variance-based approaches were used. The analysis focused on localization accuracy, communication latency, subsystem failure

rate (λ), safety threshold (ϵ_{saoe}), drilling control parameters, and multi-objective weighting factors ($\omega_1, \omega_2, \omega_3, \omega_4$). The key findings are as follows. Degrading localization accuracy from ± 10 mm to ± 50 mm (drill collar) affects throughput by around 5%, emphasizing the need for strong sensor fusion under GNSS-denied settings. Communication latency has a bigger impact on safety performance than productivity; increasing delay from 20 to 100 ms increases collision probability by 18%, highlighting the importance of low-latency edge control for real-time hazard avoidance. Sensor noise causes a $\pm 5\%$ variance in localization accuracy and productivity indicators. Increasing ω_3 (safety weight) improves S by up to 12% but decreases Q by around 7%, highlighting the productivity–safety trade-off in the objective function. Figure 9 depicts the sensitivity of system production to sensor noise change over simulation runs.

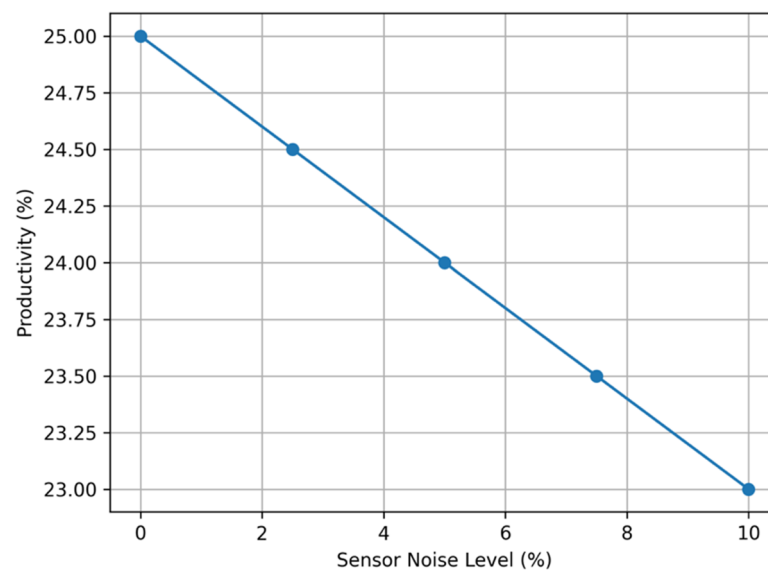


Figure 9. Sensitivity of system productivity to sensor noise changes.

5.5. Monte Carlo Robustness Evaluation

The robustness of the proposed framework was evaluated by assessing the distribution of safety constraint satisfaction across all simulation runs. The results reveal that 95.2% of runs satisfy the predefined safety constraint $P_{\text{collision}} \leq \epsilon_{\text{saoe}} = 0.05$, suggesting good operational reliability in unpredictable situations. Performance measures are consistent over the whole range of stochastic perturbations used, exhibiting robustness to environmental variability, sensor deterioration, and communication interruptions. Figure 10 shows the Monte Carlo distribution of safety constraint satisfaction throughout simulation runs. These findings support the efficiency of the uncertainty-aware optimization framework and demonstrate its appropriateness for real-world autonomous mining deployment.

While the validation is primarily simulation-based, the observed performance improvements are consistent with reported trends in industrial case studies of autonomous mining systems, particularly in terms of increased equipment utilization, reduced safety exposure, and improved operational efficiency. However, it is accepted that the lack of direct calibration against site-specific incident statistics restricts empirical validity. Future work will concentrate on integrating real-world operational data, such as incident reports and maintenance logs, to fine-tune model parameters and improve prediction reliability.

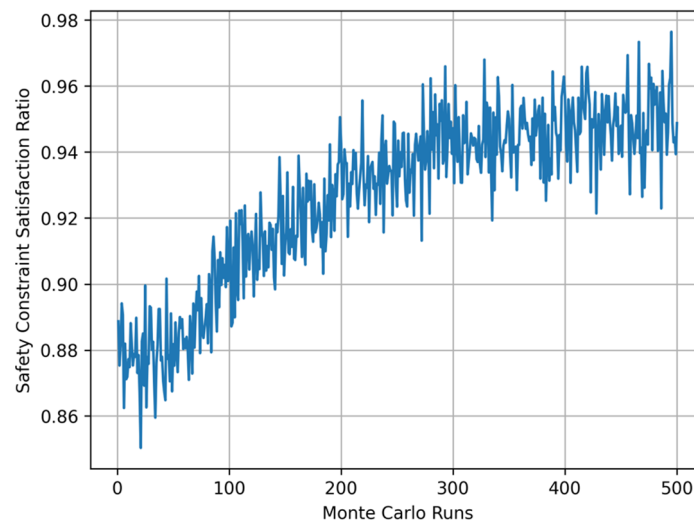


Figure 10. Monte Carlo analysis demonstrating safety constraint satisfaction.

6. Operational Performance Analysis

Section 5 provided statistical evidence of performance improvement under controlled simulated circumstances. This section interprets the results in operational terms, comparing the proposed system to real-world mining performance standards and contextualizing the outcomes within the specific constraints of surface and underground mining environments, such as Nordic climatic conditions, regulatory requirements, and economic viability. Where performance ranges are provided, they are based on industry benchmark data from published literature and operational reports, rather than repeating the simulation results from Section 5.

6.1. Surface Mining Operational Performance

When compared to established industry benchmarks, autonomous surface mining systems outperform conventional approaches significantly. Ultra-class autonomous haulage systems (AHS) with payloads ranging from 200 to 400 t achieve equipment utilization rates of 85–95%, compared to 65–75% in manually managed fleets. This improvement is primarily driven by the reduction in human-caused downtime, such as fatigue-related slowdowns, shift handovers, and procedural delays, paired with AI-driven dispatch optimization, which reduces idle time between loading and dumping cycles. Autonomous drilling systems achieve a collaring precision of ± 5 – 10 mm and angle deviation of ± 0.5 – 1° , resulting in improved blast fragmentation quality and reduced ore dilution. Adaptive adjustment of thrust (20–35 kN), rotating speed (150–300 rpm), and torque (2–6 kNm) in response to real-time rock strength data (UCS 80–300 MPa) decreases explosive usage by 10–12% when compared to fixed-parameter drilling. These gains directly contribute to the +24.3% productivity increase confirmed in Section 5.3 by eliminating rework cycles and improving material handling uniformity. The integration of autonomous excavators, haul trucks, and processing equipment through coordinated fleet management allows for continuous material flow with throughput gains of 15–20% over conventional operations, which is consistent with the simulation results shown in Section 5.3. Fuel consumption is decreased by 10–15% through optimized routing and speed profiles, while predictive maintenance saves 15–25% on maintenance costs by replacing reactive with condition-based intervention tactics.

6.2. Subterranean Mining Operations

Underground autonomous mining systems operate under significantly more stringent conditions than surface counterparts, necessitating GNSS-independent navigation, high-density sensor fusion, and safety-critical edge control within drift widths of 4–6 m. Autonomous LHD systems achieve ± 10 –20 cm navigation precision inside constrained geometries, reducing cycle time by 12–18% compared to manual operation. Payload capacities of 10–18 t each cycle, combined with AI-based fleet coordination, allow for a 25% increase in daily ore flow, directly achieving the fleet coordination improvements modeled in Section 3.2. The 48.6% safety risk reduction proven in Section 5.3 results in a considerable reduction in worker exposure to hazardous zones. Autonomous inspection systems and micro seismic monitoring networks cut exposure time in high-risk locations by 40–60%, whilst real-time geotechnical monitoring reduces ground instability risk events by about 30%. Emergency reaction time is lowered from 5 to 10 min in conventional systems to 1–3 min with autonomous monitoring, mostly due to automated alarm escalation and equipment shutdown mechanisms. These systems operate reliably at temperatures as low as $-30\text{ }^{\circ}\text{C}$, due to redundant LiDAR-IMU-SLAM localization and fault-tolerant communication networks. They address the climatic and infrastructure constraints of Nordic mining sites, as outlined in Section 1.

6.3. Comparative Operations Benchmarking

Table 5 provides a consolidated operational benchmarking comparison of conventional and autonomous mining systems, contextualizing the simulation results from Section 5 within industry performance criteria. The figures depict combined surface and subterranean operational standards derived from published industry data.

Table 5. Operational benchmarking of traditional versus autonomous mining systems.

Performance Indicator	Conventional	Autonomous	Improvement
Equipment utilization	65–75%	85–95%	+20–30%
Daily throughput	120,000–150,000 t	180,000–250,000 t	+50–67%
Fuel/energy consumption	Baseline	Optimized	–10–15%
Maintenance strategy	Reactive	Predictive	–15–25% cost
Safety incidents	High (human exposure)	Reduced (AI-driven)	–40–60%
Emergency response time	5–10 min	1–3 min	60–80% faster
Near-miss events/100k h	12–18	5–10	~–50%
Worker exposure to hazard zones	100% (baseline)	40–50%	–50–60%

6.4. Economic Viability and Cost Analysis

The economic justification for autonomous mining is evaluated using both capital expenditure (CAPEX) and operational expenditure (OPEX) aspects. Autonomous ultra-class haul trucks require a CAPEX of €4–7 million per unit, compared to €2–3 million for conventional equivalents, which includes sensor arrays, onboard digital system, and communication infrastructure. However, over the course of a typical asset’s lifecycle, operating savings more than cover the premium. Under standard Nordic mining production conditions, the 10–15% reduction in fuel consumption, 15–25% reduction in maintenance costs achieved by predictive techniques, and 50–67% increase in throughput result in average return on investment (ROI) timeframes of 3–5 years. Workforce transformation from manual to supervisory and technical jobs lowers direct labor costs while necessitating targeted upskilling investments. Table 6 shows a cost–benefit summary.

Table 6. Summary of the costs and benefits of deploying an autonomous mining system.

Benefit Metric	Conventional	Autonomous	Impact
CAPEX per haul truck	€2–3 M	€4–7 M	Higher initial cost
Equipment utilization	65–75%	85–95%	+20–30%
Throughput	120k–150k t/day	180k–250k t/day	+50–67%
Maintenance cost	Reactive baseline	Predictive	–15–25%
Fuel/energy cost	Baseline	Optimized	–10–15%
Safety-related costs	High	Substantially reduced	–40–60%
Workforce model	Manual operations	Skilled/AI-supervised	Role transition
Typical ROI period	N/A	3–5 years	Economically viable

6.5. Implementation Challenges

Despite the performance gains shown, the large-scale deployment of autonomous mining systems poses major technological, organizational, and socio-technical issues that must be handled holistically. Interoperability continues to be a significant technological obstacle. Mining operations usually rely on diverse equipment fleets purchased from several original equipment manufacturers (OEMs), which frequently span multiple generations of hardware and software. To provide seamless coordination among drilling, loading, haulage, and processing systems, innovative middleware that can harmonize a variety of sensor interfaces, communication protocols, and data formats is required. The lack of widely accepted industry standards exacerbates system complexity, integration effort, and long-term maintenance costs. Cybersecurity is another key worry as autonomous systems grow more integrated across mine-wide cyber-physical networks. Ensuring operational integrity necessitates secure communication routes, strong authentication procedures, and sturdy network topologies. These requirements are especially rigorous in Swedish mining areas, where equipment must function reliably under adverse weather conditions while adhering to strong regulatory standards. To ensure operational resilience in difficult environmental conditions such as sub-zero temperatures, low visibility, and GNSS-denied subsurface locations, redundant sensing, fault-tolerant control systems, and explicitly defined fail-safe procedures are required. These design considerations are critical for maintaining operational continuity and safe system behavior in the face of uncertainty and unanticipated interruptions. Beyond technical challenges, safety in autonomous mining systems is fundamentally socio technical. Organizational issues such as production pressure, maintenance methods, supervisory decision-making, and safety culture all influence system performance and risk propagation. The proposed system uses adaptive parameters to reflect various elements, including failure rates (λ), safety thresholds (ϵ_{safe}), and multi-objective weighting coefficients. However, explicit integration remains an open research question. Furthermore, human–automation interaction remains vital, particularly in safety-sensitive and unstructured circumstances. Human-in-the-loop supervision allows for oversight, exception management, and ethical decision-making in scenarios not fully captured by autonomous control algorithms. The transition from manual to managerial jobs necessitates personnel upskilling and organizational changes. These challenges demonstrate that the successful implementation of autonomous mining systems is dependent not only on advancements in artificial intelligence and automation technologies, but also on the

development of standardized interfaces, cyber-secure infrastructures, and organizationally aware system design frameworks. Addressing both technological and socio-technical factors is critical to developing dependable, scalable, and safe autonomous mining operations in complex, real-world settings.

While the suggested framework models safety using probabilistic risk measurements and reliability-based formulations, it is critical to recognize the limitations of reductionist techniques when dealing with complex socio-technical systems. Contemporary safety science demonstrates that failures in such systems are frequently emergent, resulting from nonlinear interactions between technical, human, and organizational factors rather than isolated component failures. The existing formulation, which is based on exponential failure rates, additive hazard structures, and set safety thresholds, is analytically tractable, but it may fail to describe systemic drift, adaptive human behavior, or unexpected interaction effects in real-world operational conditions. Future developments of this research should include complexity-aware safety models, such as system-theoretic or resilience engineering approaches, to better describe emerging risks and dynamic adaptation in autonomous mining environments. This acknowledgement establishes the suggested framework as a fundamental engineering paradigm, while also recognizing the importance of incorporating larger socio-technical dynamics for comprehensive safety assurance.

i. Legacy Risk and ALARP

The suggested architecture focuses on greenfield or fully digitalized mining environments; nevertheless, many real-world deployments occur in legacy systems with outdated equipment, fixed layouts, and historically evolved operational procedures. Legacy hazards, such as old infrastructure, insufficient sensor integration capabilities, and restricted redesign flexibility, can have a substantial impact on autonomous systems' feasibility and safety performance. To address this, the framework can be enhanced to facilitate ALARP (As Low as Reasonably Practicable) decision-making by including cost-risk trade-offs into the multi-objective optimization formulation. Safety thresholds (ϵ_{safe}) are flexible regulatory boundaries that must be balanced against economic and operational restrictions. Furthermore, stakeholder perspectives—including operators, regulators, and management—are crucial in determining acceptable risk levels and execution priorities. These viewpoints can be combined via adaptive weighting factors and constraint adjustment, allowing for context-sensitive optimization while adhering to regulatory compliance and practical feasibility. This expansion expands the suggested model's applicability to brownfield mining situations, where incremental deployment and risk-informed decision-making are critical.

7. Conclusions

This research developed a safety-constrained multi-objective optimization framework for autonomous mining systems that operate both on the surface and underground. The framework incorporates sensor fusion, edge intelligence, fleet coordination, and digital twin-based decision support into a hierarchical cyber-physical architecture that is specifically designed to operate under GNSS-denied conditions and extreme climatic constraints found in Nordic mining environments. Simulation-based validation using Monte Carlo analysis with independent runs demonstrated statistically improvements over a conventional human-operated baseline across all primary performance dimensions. Productivity increased by $24.3\% \pm 3.2\%$, energy consumption decreased by $12.8\% \pm 2.5\%$, and safety risk decreased by $48.6\% \pm 4.1\%$. Sensitivity analysis indicated that localization accuracy, communication latency, and multi-objective weighting factors are the primary determinants of system performance, with loss in localization accuracy having the greatest influence on throughput. The simulation met the established safety requirement demonstrating the resilience of the uncertainty-aware optimization approach across a variety of stochastic

operating situations. The use of autonomous haulage, precision drilling, LHD systems, and robotic inspection technologies show that it is possible to achieve high operational accuracy while reducing human exposure to dangerous situations. The Swedish operational context, with sub-zero temperatures, reduced visibility, and stringent safety and environmental regulations, provided a demanding and realistic validation environment, demonstrating the proposed framework's scalability to other highly regulated and climatically challenging mining jurisdictions. Taken together, these findings are a significant step toward fully integrated, intelligent, and robust autonomous mining ecosystems capable of sustaining next-generation sustainable resource extraction.

7.1. Novelty and Contributions

The primary contributions of this paper are as follows:

- A complete system-level framework that incorporates AI, sensor fusion, and cyber-physical control across both surface and underground mining operations, filling a significant vacuum in the literature where previous contributions have focused on isolated subsystems.
- The integrated Swedish-specific operational restrictions, such as sub-zero temperatures, limited vision, GNSS-denied conditions, and regulatory compliance requirements, to create a realistic and transportable reference model for harsh and regulation-intensive mining operations.
- The quantitative validation methodology, which includes mathematical modeling, Monte Carlo stochastic simulation, and statistical hypothesis testing, resulted in validated performance improvements of +24.3% productivity, −12.8% energy consumption, and −48.6% safety risk at 95% confidence.
- A multi-layered autonomous architecture that combines vision, edge intelligence, fleet coordination, and digital twin technologies to enable real-time, safety-constrained optimization across the whole mining value chain.
- A scalable AI-enabled system that supports predictive maintenance, dynamic routing, and coordinated multi-asset operations, serving as a transferable standard for both industrial implementation and future autonomous mining research.

7.2. Future Research Directions

- Full-system integration entails creating completely integrated surface-subsurface autonomous platforms with real-time coordination of drilling, haulage, loading, and inspection operations using a single control architecture.
- Advanced AI and learning models: Using reinforcement learning, physics-informed neural networks, and foundation models to make autonomous decisions in complex and uncertain geotechnical situations.
- Sustainability optimization entails creating energy-aware autonomous systems with the goal of lowering carbon emissions, optimizing power scheduling, and improving environmental performance in accordance with Nordic sustainability standards.
- Digital twins and simulation: Extending digital twin frameworks to mimic operational dynamics, stress redistribution, and emergency response scenarios in real-time underground mining environments.
- Cybersecurity and data governance: Develop safe, resilient communication infrastructures and established protocols to defend autonomous mining systems from cyber-physical threats.
- Human-machine collaboration: Creating supervised autonomy frameworks to balance AI-driven operational efficiency with meaningful human oversight in safety-critical mining operations.

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Nomenclature

Symbol	Description	Unit
$x_i(k)$	State vector of agent i at time step k	—
$\hat{x}_k$	Estimated system state	—
$u_i(k)$	Control input vector	—
$y_i(k)$	Measured output	—
$w_i(k), w_k$	Process noise	—
$v_i(k), v_{j,k}$	Measurement noise	—
p_k	Position vector	m
v_k	Velocity	m/s
θ_k	Orientation (heading angle)	rad
b_k	Sensor bias	—
$z_{j,k}$	Measurement from sensor j	—
$h_j(\cdot)$	Measurement model	—
$f(\cdot)$	State transition function	—
Σ_j	Measurement covariance matrix	—
$r_{i,k}$	Relative pose constraint	m
M	Number of autonomous units	—
N	Number of sensors	—
T_h	Optimization horizon	s
T_i	Task completion time	s
E_i	Energy consumption of agent i	J
R_i	Risk metric	—
α, β, γ	Weighting coefficients (fleet optimization)	—
δ_{ij}	Task assignment variable (binary)	—
$\tau_i(t)$	Travel time component	s
$P_i(t)$	Power consumption	W
$P_{\text{collision}}$	Collision probability	—
P_{failure}	Failure probability	—
ϵ_{safe}	Safety threshold	—
λ	Failure rate	s ^{−1}
$R(t)$	System reliability	—
$z(t)$	Drill penetration depth	m
$\dot{z}(t)$	Penetration rate (ROP)	m/s

F_t	Thrust force	N
F_r	Rock resistance force	N
σ_c	Compressive strength of rock	Pa
A_b	Drill bit area	m ²
k_r	Rock resistance coefficient	N·s/m
T	Torque	Nm
μ_c	Cutting friction coefficient	–
r_b	Drill bit radius	m
J_b	Rotational inertia	kg·m ²
ω	Angular velocity	rad/s
MSE	Mechanical specific energy	Pa
K_p, K_i	Control gains	–
$Q(k)$	Productivity metric	t/h
$C(k)$	Operational cost	€ or SEK
$S(k)$	Safety risk function	–
$E_m(k)$	Energy consumption	J
F_h	Haulage force	N
g	Gravitational acceleration	m/s ²
θ	Road gradient	rad
f_r	Rolling resistance coefficient	–
ω_i	Multi-objective weights	–
$\alpha(\text{energy})$	Emission conversion factor	kgCO ₂ /J
E_{CO_2}	Carbon emission equivalent	kg
X_{safe}	Safe state space	–
X_{unsafe}	Unsafe state space	–
U_{limits}	Control constraints	–

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