

Artificial Intelligence and Multi-Agent Approaches for Decision-Making and Business Process Optimization in Industrial Systems

RAKHIMA ZHUMALIYEVA, MADINA ALIMANOVA, AIKUMIS OMIRALI, BAUYRZHAN YERMAGAMBETOV, ULBOSSYN OMIRALI

Institute of Digital Transformation and Artificial Intelligence
Narxoz University
55, Zhandossov Street, Almaty, Kazakhstan, 050035
KAZAKHSTAN

Abstract: - This study develops a conceptual and simulation-based framework for intelligent decision-making and process optimization in mineral processing systems. The framework integrates artificial intelligence, multi-agent coordination, adaptive control, and digital twins to support real-time optimization under uncertain and variable operating conditions. Systems analysis, mathematical modeling, simulation, and industrial data-processing methods are combined, while two-sample t-statistics assess differences between baseline and proposed scenarios across 50 independent simulation runs. The proposed architecture coordinates technological units, adjusts equipment parameters, and applies predictive analytics to decision support. Simulation results indicate improvements in resource utilization, energy efficiency, production stability, and product quality. By using production monitoring data and digital-twin representations, the framework supports industrial digital transformation without additional laboratory experiments and provides a basis for intelligent control and business-process optimization in mining and metallurgical operations.

Key-Words: - Artificial intelligence, Adaptive control, Multi-agent systems, Digital twins, Process optimization, Digital transformation, Business analytics.

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1 Introduction

Modern mining and metallurgical systems operate under highly variable raw material conditions while maintaining a balance among recovery, product quality, energy efficiency, and environmental performance. Under such conditions, traditional control approaches based on fixed models and predefined operating regimes become less effective, particularly in environments characterized by uncertainty and continuously changing constraints.

At the same time, the development of Industry 4.0 has led to a shift in how industrial processes are monitored and controlled [1]. Technologies such as artificial intelligence (AI), machine learning (ML), digital twins, and cyber-physical systems are increasingly being used to enhance decision-making processes and support data-driven business optimization. In this context, a digital twin is commonly understood as a dynamic virtual representation of a physical system that interacts with real-time data, enabling simulation, prediction, and decision support throughout the lifecycle of industrial assets [2].

In recent years, digital twins have found growing application in mining and mineral processing. Their

use makes it possible to improve operational efficiency, reduce energy consumption, and maintain more stable process performance under variable feed conditions. Digital twins have been successfully applied to modeling comminution, flotation, and separation processes, where they support scenario analysis and predictive decision-making [3], [4].

Moreover, artificial intelligence methods have become an essential component of modern process analytics. Machine learning algorithms, including neural networks and ensemble methods, are widely used to model complex relationships between ore characteristics and technological performance indicators. These methods improve prediction accuracy, increase system adaptability, and support automated decision-making under uncertain conditions.

An important and actively developing direction is the use of multi-agent systems (MAS). In such systems, individual components of the production process are represented as autonomous agents capable of local decision-making and interaction within a distributed environment. For example, individual agents may represent grinding, flotation, or classification stages. Through coordinated interaction,

these agents support system-level optimization while maintaining flexibility, robustness, and distributed decision-making capabilities [5]. Despite recent advances, integrated approaches combining digital twins, AI-based predictive models, and multi-agent coordination within a unified decision-making framework remain insufficiently developed. Many existing studies have mainly focused on isolated process stages or single optimization objectives, while data-driven smart manufacturing emphasizes the interdependence between technological units across the production chain [6].

In practice, mineral processing plants function as highly interconnected systems in which changes in one process unit can influence the entire production chain. These interactions create complex feedback mechanisms and time delays, which are difficult to capture using isolated models. This highlights the need for integrated solutions capable of simultaneously handling local control tasks, optimizing system-wide decision-making, and creating business value.

Unlike most existing studies that focus on isolated optimization problems or individual process stages, this work develops a unified conceptual multi-agent digital twin framework integrated with AI-based predictive mechanisms for coordinated decision-making across interconnected processing units.

A key limitation of existing approaches is the insufficient integration between predictive analytics, artificial intelligence methods, and real-time decision-making mechanisms. Although digital twins provide detailed simulation capabilities and AI models offer strong predictive performance, their effective integration within multi-agent architectures remains an emerging research area [7]. In addition, many approaches rely on simplified assumptions and do not fully account for uncertainties such as feed variability, equipment wear, and stochastic disturbances.

For these reasons, the development of integrated intelligent systems that combine artificial intelligence, digital twins, and multi-agent coordination is of both scientific and practical interest. Such systems can support adaptive process control, improve coordination between technological units, and enhance real-time decision-making efficiency and business performance outcomes. In this study, a multi-agent AI-based framework is proposed for adaptive optimization of mineral processing operations through the integration of digital twin models and data-driven decision-making mechanisms.

In this context, the aim of this study is to develop and investigate an artificial intelligence-based approach for optimizing technological processes in mineral processing plants through the integration of

multi-agent systems, digital twin models, and data-driven decision-making mechanisms.

To achieve this aim, the following research questions are addressed: How can a multi-agent approach improve coordination between interconnected technological units in mineral processing systems? To what extent can artificial intelligence and digital twin technologies enhance the adaptability and efficiency of process control under variable operating conditions? How can data-driven models be integrated into real-time decision-making to support both technological and business decision optimization processes?

These research questions define the direction of the study and provide the basis for the problem formulation and the development of the proposed approach.

Accordingly, this study addresses the problem of developing a conceptual and simulation-based framework for intelligent decision-making and process optimization in industrial systems, aiming to overcome the limitations of conventional control approaches in complex industrial environments.

2 Problem Formulation

2.1 Characteristics of Mineral Processing Systems as Complex Business Processes

Mineral processing plants represent complex socio-technical systems that can be interpreted not only as engineering infrastructures but also as integrated business processes aimed at maximizing economic value generation. In this context, each technological stage contributes to overall system performance through its impact on recovery rates, product quality, operational costs, and energy efficiency.

From a business analytics perspective, system performance is evaluated using technical and economic indicators such as cost per ton of processed ore, energy consumption per unit of output, equipment utilization, and process stability indices. These indicators reflect the transformation of technological operations into measurable business outcomes, making the system inherently multi-dimensional and value-oriented.

A key characteristic of mineral processing systems is the strong interdependence between process units, which can be formally interpreted as a distributed production network of interacting agent-based components. Each stage influences subsequent operations, forming tightly coupled feedback loops. For example, variations in grinding fineness directly affect flotation efficiency and final concentrate

quality. As a result, local optimization does not necessarily lead to global performance improvement.

This interconnected structure requires coordinated decision-making across all stages, where each process unit is represented as a decision-making agent within a distributed architecture. These agents operate in conjunction with digital twin models and data-driven analytics to support predictive and adaptive decision-making.

Additionally, variability in raw material composition introduces significant uncertainty in operational performance, as changes in ore grade, mineralogical structure, and particle size distribution lead to fluctuations in key process indicators. These uncertainties highlight the need for adaptive, data-driven decision-support systems capable of continuous adjustment and learning.

Most existing studies focus on individual optimization strategies or loosely coupled digital twin models, whereas this work develops a unified multi-agent digital twin framework enabling coordinated decision-making across interconnected processing stages.

2.2 Limitations and Challenges of Classical Control and Optimization Approaches

Traditional control and optimization approaches in industrial systems are typically based on static, semi-empirical, or model-driven methodologies with predefined operating regimes. While such approaches may perform adequately under stable conditions, they are not suitable for modern industrial environments characterized by high uncertainty, nonlinear dynamics, and frequent operational variability [8].

In mineral processing systems, fluctuations in feed composition, equipment degradation, and environmental disturbances significantly reduce the accuracy and robustness of conventional control strategies. As a result, these methods often fail to maintain optimal performance under real-world operating conditions, particularly when system dynamics evolve over time.

From a business process optimization perspective, a major limitation of existing approaches is the weak integration between data acquisition, analytical modeling, and decision-making mechanisms. In many industrial systems, monitoring and control are implemented as separate functional layers, which leads to delayed responses to process deviations and suboptimal operational adjustments.

Furthermore, the lack of real-time integration between analytics and control results in underutilization of available industrial data, including high-frequency sensor data and historical operational records. This limits the ability of systems to generate

actionable insights and reduces overall decision-making efficiency.

Another fundamental limitation is that conventional optimization methods are often designed for single-objective problems, focusing on isolated criteria such as cost reduction or throughput maximization. However, real industrial systems require simultaneous optimization of multiple conflicting objectives, including product quality, energy consumption, and process efficiency in mineral processing operations [9], [10], [11].

In addition, many classical approaches rely on assumptions such as stationarity, convexity, or complete knowledge of system dynamics, which are rarely satisfied in practice. These limitations significantly reduce their applicability in complex, large-scale industrial environments.

Finally, traditional control architectures are predominantly centralized and hierarchical, which creates scalability constraints and reduces system resilience. Such architectures are not well suited for distributed industrial environments where decision-making must occur at multiple levels and time scales simultaneously.

The key limitations of conventional control and optimization approaches are systematically summarized in Table 1.

Table 1. Comparison of Conventional and AI-Based Control Approaches

#	Criterion	Conventional Control	AI-Based Multi-Agent Approach
1	Decision-making principle	Rule-based and predefined	Adaptive and data-driven
2	System architecture	Centralized	Distributed multi-agent
3	Response to disturbances	Reactive	Predictive and adaptive
4	Handling of uncertainty	Limited	Dynamic and continuous
5	Coordination between process units	Weak	Coordinated inter-agent interaction
6	Optimization strategy	Single-objective	Multi-objective optimization
7	Scalability	Limited	High
8	Use of real-time data	Partial	Continuous real-time integration
9	Support for predictive analytics	Minimal	Integrated AI-based prediction
10	System flexibility	Low	High

Source: created by the authors

2.3 Formulation of the AI-Based Optimization Problem

Building on the identified limitations, this study introduces a structured conceptual framework that integrates multi-agent coordination, digital twin modeling, and AI-based predictive decision-making into a unified optimization architecture. The studied problem is formally formulated as the development of an intelligent, data-driven decision-support framework for mineral processing systems operating under conditions of uncertainty, variability of raw material properties, and strong interdependence between technological units. The system is required to ensure adaptive coordination of distributed process stages while simultaneously optimizing both technological and business performance indicators [12], [13].

Formally, the mineral processing system can be represented as a dynamic, partially observable environment consisting of a set of interacting technological units $\{U_i\}$, each associated with an intelligent agent A_i . Each agent performs local state monitoring, data processing, and generation of control actions based on partial observations, local objective functions, and shared global performance targets. The overall system behavior emerges from the coupled interaction of these agents within a distributed decision-making space.

The primary objective of the proposed framework is to maximize overall system performance under multiple, often conflicting criteria. These include operational efficiency (e.g., recovery rate and throughput), energy efficiency (specific energy consumption), product quality stability, and resource utilization efficiency. At the same time, the system must minimize operational costs, process variability, and the impact of disturbances arising from fluctuations in ore composition and equipment conditions.

This leads to a multi-criteria optimization problem, where decision-making is not restricted to a single objective but involves simultaneous consideration of several performance dimensions. In this context, the system must continuously maintain a balance between the local optimization of individual process units and the global optimization of the overall production chain. The interdependence between units implies that decisions made at one stage directly influence the performance of subsequent stages, which excludes the possibility of independent optimization.

To address this challenge, a distributed optimization paradigm is introduced, where each agent performs local decision-making based on partial information while participating in a coordinated global strategy through inter-agent communication

mechanisms. This structure allows the system to maintain scalability and robustness while ensuring coherence of global objectives.

A key requirement of the proposed system is the ability to operate under uncertainty. Sources of uncertainty include variability in feed grade and mineralogical composition, measurement noise in sensor data, incomplete observability of process states, and stochastic disturbances in equipment behavior. Therefore, the decision-making framework must incorporate predictive and adaptive mechanisms capable of updating control strategies in real time based on newly available information.

Within this formulation, digital twin models play a critical role as computational representations of physical process units. They provide a simulation-based environment for evaluating system behavior under different operational scenarios, enabling prediction of process outcomes and supporting proactive decision-making. Digital twins are continuously updated using real-time and historical data, ensuring consistency between the physical system and its virtual representation [14], [15].

The multi-agent system operates based on distributed intelligence, where each agent combines local data processing, predictive analytics, and interaction with other agents to achieve coordinated behavior. This coordination is essential for aligning local actions with global performance objectives, particularly in situations where conflicting goals arise between different stages of the production process.

Mathematically, the problem can be interpreted as a constrained dynamic optimization task in which the system seeks an optimal control policy $\pi(t)$ that maps observed states of the system to control actions over time. The optimal policy must satisfy both operational constraints imposed by technological limitations and performance constraints defined by business and production objectives. However, due to the high complexity and uncertainty of the system, an explicit analytical solution is not feasible, which justifies the use of simulation-based and AI-driven approximation methods.

In summary, the formulated problem represents a distributed, multi-objective, and uncertainty-driven optimization task in which artificial intelligence, multi-agent coordination, and digital twin technologies are jointly applied to achieve adaptive control and improved decision-making in mineral processing systems. This formulation establishes the theoretical foundation for the subsequent methodological development, algorithmic design, and scenario-based evaluation presented in the study [12], [13], [14], [15].

3 Problem Solution

3.1 Methodological Framework of the Study

The study is based on a system-oriented methodological framework aimed at analyzing the behavior of intelligent digital geometallurgical systems under conditions of uncertainty, variability, and distributed decision-making. The proposed approach integrates principles of multi-agent systems and digital twin technologies as key enablers of intelligent industrial architecture.

The methodological foundation is based on the representation of the mineral processing system as a distributed environment composed of interacting autonomous agents operating across multiple hierarchical levels. Each agent is responsible for a specific functional domain, including data acquisition, process modeling, predictive analytics, and decision coordination. The overall system behavior emerges from the interaction between these agents rather than from centralized control mechanisms, which is consistent with established multi-agent system paradigms and digital twin-agent integration concepts [5].

A key methodological principle of the study is the use of a simulation-based experimental design, which enables the evaluation of system behavior under controlled and repeatable conditions. This approach is particularly suitable for complex industrial systems where real-world experimentation is costly, risky, or infeasible. Digital twin environments provide the computational basis for simulating physical processes and supporting decision analysis under dynamic conditions [16]. The evaluation framework is based on comparative scenario analysis, in which alternative decision-making paradigms are assessed under identical operational conditions.

This enables the identification of differences in system performance resulting from the adoption of multi-agent coordination and artificial intelligence-based control mechanisms.

The methodological framework also incorporates a multi-level perspective, distinguishing between operational, analytical, and coordination layers of the system. This hierarchical structure provides a basis for analyzing how local decisions at the agent level contribute to global system performance outcomes.

Overall, the proposed methodological framework establishes a unified foundation for scenario design, simulation modeling, performance evaluation, and statistical analysis, ensuring consistency across all stages of the study.

3.2 Scenario Design and Experimental Framework

To evaluate the proposed intelligent digital geometallurgical system, a structured scenario-based experimental framework is developed. The approach is based on comparative analysis of alternative decision-making paradigms under controlled simulation conditions.

Two operational scenarios are considered to represent fundamentally different control and decision-making strategies in mineral processing systems.

Scenario 1 (Baseline): The baseline scenario reflects a conventional process control paradigm based on predefined operational regimes, static decision rules, and limited integration of analytical and predictive tools. Decision-making is primarily reactive and relies on historical operational knowledge and semi-empirical models. In this configuration, inter-unit coordination is weakly formalized, which limits adaptability under conditions of variability in ore properties and process disturbances.

Scenario 2 (Proposed): The proposed scenario is based on an AI-driven multi-agent decision-making framework integrating predictive analytics, digital twins, and distributed control logic. Each technological unit is represented as an autonomous agent capable of local decision-making, continuous data processing, and inter-agent interaction. Global coordination emerges through iterative information exchange and alignment of local objectives with system-level performance criteria. This enables adaptive and self-organizing process control under dynamic operating conditions [17].

The scenarios represent a conceptual transition from rule-based control systems toward data-driven, adaptive, and distributed intelligence architectures, which is a key direction in the digital transformation of industrial systems [18]. The comparative characteristics of the baseline and proposed scenarios are summarized in Table 2.

Table 2. Functional Structure of the Proposed Multi-Agent System

#	Agent Type	Main Function	Input Data	Output Actions
1	Grinding Agent	Control of grinding parameters	Ore hardness, particle size	Mill operating adjustments
2	Flotation Agent	Optimization of flotation performance	Reagent dosage, pulp properties	Flotation control actions
3	Classification Agent	Particle classification management	Size distribution data	Separator parameter updates
4	Predictive Analytics Agent	Forecasting process behavior	Historical and real-time data	Predictive recommendations
5	Coordination Agent	Global optimization and synchronization	Data from all agents	Coordinated system decisions
6	Digital Twin Module	Simulation and scenario analysis	Process and sensor data	Virtual process states

Source: created by the authors

The analysis is conducted in a simulation-based environment and is not intended for a specific industrial implementation. Instead, it provides a generalized experimental framework for comparative evaluation of decision-making strategies under uncertainty.

3.3 Performance Metrics and Evaluation Indicators

The effectiveness of the proposed system is evaluated using a set of key performance indicators reflecting operational efficiency, energy utilization, and process stability. These indicators are selected to enable a comprehensive evaluation of system performance under different decision-making strategies within the multi-agent framework.

Operational efficiency is evaluated using indicators such as recovery rate, throughput, and resource utilization efficiency across the processing chain. These metrics reflect the ability of the system to maximize valuable component extraction while maintaining efficient use of raw materials under

variable geological conditions. Adaptive coordination among agents enables dynamic adjustment of process parameters, which directly influences recovery performance and material losses.

Energy efficiency is defined in terms of specific energy consumption per unit of processed material. This indicator captures the effectiveness of energy management in energy-intensive operations such as crushing, grinding, and flotation. The integration of predictive models and distributed decision-making mechanisms enables optimization of energy usage, reduction of unnecessary operational loads, and improved overall energy performance of the system.

Process stability is characterized by the variability of key technological parameters and the consistency of product quality output. Stability is a critical requirement in metallurgical systems due to inherent variability in ore composition and process conditions. The proposed multi-agent architecture enhances stability through continuous monitoring of system states, detection of deviations, and real-time corrective actions across distributed process units.

Collectively, these indicators form a multi-dimensional evaluation framework that links system intelligence, operational performance, and industrial efficiency, enabling consistent comparison of alternative decision-making paradigms. The definition and interpretation of the key performance indicators are summarized in Table 3.

Table 3. Key Performance Indicators Used for System Evaluation

#	Performance Indicator	Description	Optimization Objective
1	Recovery Rate	Valuable component extraction efficiency	Maximization
2	Throughput	Amount of processed material	Maximization
3	Specific Energy Consumption	Energy used per ton of ore	Minimization
4	Process Stability	Variability of process indicators	Minimization
5	Product Quality Stability	Consistency of concentrate quality	Maximization
6	Resource Utilization Efficiency	Efficiency of raw material usage	Maximization
7	Operational Cost	Cost of process operation	Minimization

Source: created by the authors

3.4 Data Processing and Simulation Framework

The evaluation is based on simulation modeling of mineral processing operations using production-like datasets and digital twin representations of technological units. The digital twin framework enables the generation of multiple operational scenarios under varying input conditions, including changes in raw material characteristics, feed variability, equipment states, and stochastic disturbances. This approach is widely used for the analysis of complex cyber-physical industrial systems [11].

Each scenario is evaluated using N independent simulation runs ($N = 50$) to ensure statistical robustness and reduce the influence of random variability. Stochastic disturbances are introduced through controlled random variations in key input parameters, including ore grade, mineralogical composition, particle size distribution, and equipment performance deviations. These disturbances are modeled using predefined probability distributions consistent across all simulation scenarios.

For each simulation run, the system executes a full operational cycle of the mineral processing process, represented as a time-stepped dynamic model. The digital twin components continuously update process states based on incoming simulated sensor data and agent-based control actions. This enables the generation of consistent time-series datasets describing the evolution of key performance indicators under both baseline and proposed control strategies.

The simulation framework is implemented as an iterative process, where each iteration represents a complete system cycle. Convergence of the simulation is defined by the stabilization of key state variables and performance indicators within a predefined tolerance threshold over consecutive iterations. This ensures that the system reaches a quasi-steady operational regime before performance data are extracted for statistical evaluation [19].

Data processing includes normalization, synchronization, and filtering of heterogeneous data streams originating from different process units and agent modules. This ensures consistency between low-level operational data and aggregated system-level performance indicators. The resulting dataset provides a structured basis for comparative analysis of alternative decision-making strategies under identical experimental conditions.

Overall, the simulation framework ensures reproducibility, consistency, and comparability of results, forming a robust foundation for subsequent

statistical evaluation of the proposed intelligent digital geometallurgical system.

3.5 Statistical Evaluation Using T-Statistics

The comparative assessment of the baseline and proposed approaches is conducted using a statistical evaluation framework applied to simulation-generated datasets. Since the proposed system includes AI-based components, including predictive analytics and multi-agent decision-making mechanisms, its performance is assessed using both AI statistical tools [20], [21] and standard statistical methods [22].

The analysis is based on repeated simulation experiments performed under identical operational conditions. This procedure allows the generation of multiple observations for each key performance indicator, including recovery rate, energy consumption, and process stability.

For each scenario, multiple simulation runs are executed under varying input conditions, including fluctuations in raw material properties, process disturbances, and system states. As a result, two corresponding empirical datasets are obtained for the baseline and the proposed multi-agent-based approach. These datasets represent distributions of system performance indicators rather than single deterministic values, which is essential for capturing the stochastic nature of industrial process simulation.

The considered performance indicators may exhibit potential interdependencies due to shared process dynamics across technological units, which implies a partially multivariate structure of the evaluation space. This multivariate nature suggests that advanced statistical techniques such as ANOVA or MANOVA may be considered in future extensions of this work when explicit modeling of interdependencies between performance indicators is required. However, in this study, the statistical assessment is performed at the level of individual performance indicators to ensure interpretability and transparent comparison between scenarios.

The main objective of the statistical evaluation is to determine whether the observed differences between the two scenarios are systematic and consistent, or whether they arise from random variability inherent in the simulation environment. Accordingly, the analysis focuses on verifying the robustness of performance improvements achieved by the proposed approach across repeated experiments.

For each performance indicator, sample mean values and variances are calculated for both scenarios [21], [22]. These aggregated statistics provide the basis for quantitative comparison of system performance under baseline and proposed

configurations.

To formalize this comparison, the standard two-sample t-statistic is applied:

$$t = (\bar{X}_1 - \bar{X}_2) / \sqrt{(s_1^2/n_1) + (s_2^2/n_2)} \quad (1)$$

where $\bar{X}_1$ and $\bar{X}_2$ denote the mean values of the considered performance indicator for the baseline and proposed scenarios, respectively; s_1^2 and s_2^2 represent the corresponding sample variances; and n_1 and n_2 are the number of simulation runs in each scenario [21], [22].

The null hypothesis assumes that there is no statistically significant difference between the two scenarios in terms of the evaluated performance indicators, while the alternative hypothesis assumes that the proposed multi-agent framework leads to improved system performance [22].

The calculated t-statistics are used to assess the magnitude of differences between the two distributions of simulation results. If the absolute value of the t-statistic exceeds the critical threshold corresponding to a predefined confidence level (typically 95%), the null hypothesis is rejected, indicating a statistically significant improvement.

Within the conceptual nature of this study, the t-statistical framework is not intended to represent real industrial measurements but rather provides a formalized and reproducible mechanism for comparing alternative decision-making strategies in a controlled simulation environment. This ensures methodological rigor and supports consistent interpretation of performance differences across scenarios.

The statistical evaluation is performed within a reproducible simulation environment characterized by a fixed number of independent runs, controlled stochastic disturbances, and predefined convergence criteria as described in the methodological framework, ensuring consistency and comparability of results across scenarios [21], [22].

Overall, the integration of simulation-based data generation and statistical hypothesis testing provides a coherent framework for assessing the effectiveness of the proposed intelligent digital geometallurgical system under uncertainty and variable operating conditions.

3.6 Interpretation in the Context of Business Analytics

From a business analytics perspective, the results of the statistical evaluation provide a quantitative basis for assessing how changes in decision-making mechanisms influence system-level performance. The observed statistically significant differences between the baseline and proposed scenarios indicate that the integration of AI-driven multi-agent coordination

leads to measurable improvements in operational indicators under simulation conditions.

Improvements in operational efficiency, expressed through increased recovery rates and improved resource utilization, directly translate into higher material output and more efficient use of raw materials. These effects reflect the ability of the proposed system to better adapt process parameters to variable input conditions through distributed decision-making.

At the same time, reductions in specific energy consumption demonstrate improved efficiency of energy-intensive operations such as grinding and flotation. This indicates that coordinated agent-based control contributes to more efficient allocation of energy resources and reduced operational redundancy under dynamic conditions.

Process stability improvements, reflected in reduced variability of key technological indicators, suggest more consistent system behavior across simulation runs. This reduces the likelihood of extreme deviations in product quality and improves the predictability of system performance under uncertain operating conditions.

From an analytical standpoint, the integration of simulation-based modeling with statistical evaluation enables a structured comparison of alternative decision-making strategies [23]. This provides a formal mechanism for linking operational indicators with system-level performance outcomes, allowing the quantification of relative improvements rather than purely descriptive assessment.

In this context, the proposed framework supports a transition from static performance evaluation toward comparative, model-based business analytics. The combination of multi-agent coordination, digital twin simulation, and statistical testing allows performance differences to be interpreted in a consistent and reproducible manner.

Overall, the results demonstrate that improvements at the level of decision-making architecture propagate to both operational and, more broadly, business-relevant indicators, confirming the usefulness of AI-based multi-agent systems for enhancing performance in complex industrial environments [24], [25].

4 Conclusion

This study presented an artificial intelligence-based framework for decision-making and business process optimization in mineral processing systems, integrating multi-agent coordination mechanisms and digital twin modeling within a unified simulation environment [26], [27]. The proposed approach was motivated by the limitations of conventional control

strategies, which are insufficient for handling uncertainty, strong interdependencies between process units, and dynamic variability of raw material properties [27], [28], [29].

The results of the study demonstrate that the combination of multi-agent systems and digital twin technologies enables more adaptive and distributed decision-making compared to traditional centralized approaches. In particular, the proposed framework supports improved coordination between technological units, allowing local decisions to be aligned with global system-level objectives.

The comparative scenario analysis, supported by statistical evaluation, demonstrates that the proposed approach provides consistent improvements in key performance indicators, including operational efficiency, energy consumption, and process stability. These results confirm that improvements in system-level intelligence can lead to measurable enhancements in both technological and business performance.

From a methodological perspective, the study shows that simulation-based evaluation combined with statistical comparison provides a reliable and reproducible mechanism for assessing alternative decision-making strategies in complex industrial environments. This is particularly relevant for systems where real-world experimentation is limited or infeasible.

In summary, the findings support the hypothesis that artificial intelligence and multi-agent coordination, when integrated with digital twin representations of industrial processes, can significantly improve the adaptability and efficiency of mineral processing systems. The proposed framework contributes to the development of intelligent, data-driven industrial systems capable of operating under uncertainty while maintaining both operational performance and economic efficiency.

Future work may focus on extending the proposed approach toward real-time industrial implementation, incorporating reinforcement learning-based decision policies, and validating using real operational datasets from industrial mineral processing plants.

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Conflict of Interest

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