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Conceptual Design of IDGMS based on Multi-Agent Technologies

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Abstract: *This research paper presents a conceptual framework for an Intelligent Digital Geometallurgical System (IDGMS) integrating multi-agent algorithms and digital twins. The proposed architecture is organized into three hierarchical levels—operational, analytical, and coordination-control—connected through a unified information and semantic data bus, ensuring end-to-end data flow, semantic interoperability, and robust decision-making under uncertain and dynamic conditions. At the operational level, agents perform real-time data acquisition, filtering, calibration, and geospatial referencing from sensors, laboratory systems, IIoT devices, and equipment telemetry. The analytical level implements predictive analytics, geostatistical modeling, three-dimensional geomodeling, and digital twins, enabling scenario-based evaluation and adaptive process control. The coordination-control level aggregates analytical results, executes multi-criteria optimization, and generates strategic decisions, ensuring alignment of production objectives and resource allocation. The integration of digital twins provides a virtual environment for "what-if" scenario analysis, continuous model refinement, and predictive adjustment of technological regimes. Ontology-driven data unification enhances semantic consistency across heterogeneous data sources, reducing ambiguity in agent interactions. The proposed multi-agent IDGMS demonstrates high adaptability, self-regulation, and predictive capability, offering a scientific basis for improving geometallurgical modeling, optimizing metallurgical processes, and enhancing the digital maturity and operational efficiency of mining and metallurgical enterprises.*

Key Words: *Intelligent Digital Geometallurgical System (IDGMS); Multi-Agent Systems (MAS); Digital Twins; Geometallurgy; Mining and Metallurgical Industry (MMI).*

I. INTRODUCTION

The mining and metallurgical industry is undergoing an accelerated digital transformation driven by increasing geological complexity of ore bodies, declining ore grades, rising operational costs, and growing requirements for sustainability and production efficiency. Modern mining operations are characterized by high variability in mineralogical and technological parameters, uncertainty in geological information, and strong interdependencies between mining, processing, and metallurgical stages. Under these conditions, traditional deterministic models and isolated automation systems are no longer sufficient to ensure stable performance and optimal decision-making across the entire production chain.

Geometallurgy has emerged as a systemic approach that integrates geological, mineralogical, technological, and economic data to improve the predictability and controllability of ore processing behavior. However, the practical implementation of geometallurgical concepts at an industrial scale remains challenging due to heterogeneous data sources, fragmented digital infrastructures, limited adaptability of existing information systems, and the lack of unified mechanisms for real-time data integration, analysis, and decision support. Conventional SCADA-, MES-, and ERP-based solutions typically operate within siloed architectures and provide limited support for predictive analytics, scenario-based optimization, and adaptive control of complex production systems.

Recent advances in artificial intelligence, distributed computing, and digital twin technologies have created new opportunities to address these challenges. In particular, multi-agent systems (MAS) offer a promising paradigm for managing complex, dynamic, and distributed environments by enabling autonomous yet coordinated decision-making among specialized computational agents. When combined with digital twins of mineral deposits, processing equipment, and beneficiation plants, multi-agent architectures enable continuous synchronization between physical and virtual production environments, supporting predictive modeling, scenario evaluation, and proactive control of technological processes.

This paper proposes a conceptual architecture for an Intelligent Digital Geometallurgical System (IDGMS) based on a multi-agent approach and the integration of digital twins. The proposed architecture is organized as a three-level hierarchy operational, analytical, and coordination-control levels—connected through a unified information and semantic data bus. Such an organization ensures end-to-end data flow, semantic interoperability, and coordinated interaction between heterogeneous agents operating under conditions of high uncertainty and rapidly changing geometallurgical parameters. Ontology-driven data integration provides a common semantic framework for geological, mineralogical, technological, and economic information, reducing ambiguity in data interpretation and enabling consistent decision-making across system components.

At the operational level, autonomous agents perform real-time data acquisition, filtering, calibration, and geospatial referencing using inputs from sensors, laboratory systems, IIoT devices, and equipment telemetry. The analytical level focuses on the development of digital geometallurgical models, predictive analytics, and digital twins, employing geostatistical modeling, three-dimensional geomodeling, and machine learning methods to forecast process behavior and evaluate production scenarios. The coordination-control level aggregates analytical results and implements distributed optimization and strategic decision-making, translating multi-criteria optimization outcomes into control actions for mining and processing operations.

A key feature of the proposed architecture is the integration of a network of digital twins at multiple scales, enabling what-if scenario analysis, continuous model refinement, and predictive control of geometallurgical processes. Hybrid inter-agent communication mechanisms, combining direct FIPA ACL–compatible protocols with indirect coordination through an integration bus, ensure scalability, robustness, and efficient information exchange in high-load industrial environments. The separation of operational, tactical, and strategic information flows further enhances system adaptability and supports decision-making across different time horizons.

The objective of this study is to develop a scientifically grounded conceptual framework for a multi-agent Intelligent Digital Geometallurgical System capable of adaptive, predictive, and self-regulating operation. The proposed architecture aims to improve the accuracy of geometallurgical modeling, enhance coordination between production stages, reduce technological and economic risks, and support the long-term digital maturity and operational efficiency of mining and metallurgical enterprises.

II.MATERIAL AND METHODS

Domain analysis and formulation of architectural requirements

The design of an intelligent digital geometallurgical system begins with an in-depth analysis of the subject domain, which includes not only the study of the structure of geometallurgical data but also a comprehensive assessment of the entire production environment. At this stage, the key objective is to identify the logic of data formation, patterns of spatial and temporal variability of ore bodies, characteristics of mineral composition, parameters of beneficiation and metallurgical processes, as well as digital constraints that determine the capabilities of the future multi-agent architecture. The subject domain is considered a multi-level system in which natural geological objects, technological operations, and digital components form a complex information space that requires a unified approach to data interpretation and integration.

The first step is an audit of the enterprise's existing digital infrastructure. The condition of sensors, automated control systems, laboratory complexes, mining equipment, geological exploration tools, and geomodeling systems is analyzed. Particular attention is paid to the availability of data in digital form, the formats used, the consistency of data storage structures, and the methods applied for data validation. A key challenge often proves to be data fragmentation: geological exploration results are stored in one set of systems, drilling and blasting parameters in others, and laboratory analyses and technological parameters in yet others. This creates significant obstacles to building an end-to-end digital model, as the lack of standardized data exchange protocols leads to inconsistencies in information flows and reduces the effectiveness of subsequent multi-agent coordination.

At the level of subject-domain analysis, patterns of uncertainty emergence in the data are identified. Geological data are subject to natural variability, technological data depend on equipment condition, cycle time, and human factors. Beneficiation data may contain errors due to fluctuations in sample quality, imperfections of analytical methods, or equipment malfunctions. All these characteristics shape the requirements for the multi-agent architecture, including the need for noise robustness, support for streaming data processing, recovery of missing values, and assessment of data source reliability.

A critically important element is the identification of key business requirements for the system. Mining and metallurgical enterprises face a wide range of tasks, including ore quality forecasting, optimization of transportation routes, planning of beneficiation regimes, loss reduction, monitoring of technological process stability, and evaluation of economic parameters. Each task generates specific requirements for agent functionality, message structures, and data processing methods. For example, a geostatistical agent must operate with spatial models, a forecasting agent with time series, and an optimization agent with combined parameters. Therefore, subject-domain analysis does not merely precede architectural design but fundamentally determines its structure.

An important component of the analysis is the modeling of current information flows. Based on process analysis, a scheme is developed that reflects the movement of data from the source to the end user. Such a scheme makes it possible to identify bottlenecks, delays, information duplication, and inefficient routing. For instance, delays in laboratory data delivery reduce the speed of technological regime adjustments. The absence of a unified data validation point creates the risk of transmitting unreliable information between agents. Consequently, the architecture of the future intelligent digital geometallurgical system must include modules for verification, filtering, reliability ranking, and automated data quality control.

The final aspect is the formulation of functional and non-functional requirements. Functional requirements include data acquisition, synchronization, preprocessing, analysis, and forecasting. Non-functional requirements include processing speed, fault tolerance, security, data protection, scalability, and integration with other enterprise digital platforms. Based on these requirements, a specification is developed that defines the key parameters of the multi-agent architecture, including the number of agents, their specialization, interaction algorithms, and level of autonomy.

Thus, subject-domain analysis forms the foundation for building an effective architecture of an intelligent digital geometallurgical system. This analysis ensures a deep understanding of processes, identifies constraints, defines requirements, and provides the basis for subsequent design stages. Without this stage, a multi-agent system may prove insufficiently adaptive, insufficiently integrated, or incapable of addressing real production challenges.

Conceptual design of a multi-agent architecture

The second key stage of the methodology is associated with the development of the system's conceptual architecture, within which agent roles, the structure of their interactions, message exchange logic, the formation of an ontological model, and the development of basic interaction protocols are defined. Conceptual design is aimed at establishing a high-level system structure capable of ensuring autonomy, coherence, and adaptability of all components under conditions of high variability in data and processes typical of the mining and metallurgical industry.

The first step is the development of an ontology of geometallurgical data. The ontology serves as the foundation for a unified understanding of terms, objects, and the relationships between them. It includes a glossary of key concepts, mineral classifications, types of technological variables, ore parameters, descriptions of beneficiation stages, and links between quality indicators and their impact on production processes. The ontology ensures semantic interoperability among agents, enabling them to interpret data consistently and avoid ambiguity. For example, the term "Fe_total" may be interpreted differently in laboratory systems, pit models, and processing units. The ontology eliminates such inconsistencies, ensuring correctness of agent interactions at the semantic level.

The next stage is the identification of agent types and their allocation according to functional roles. In a typical intelligent digital geometallurgical system (IDGMS) architecture, the following groups of agents can be distinguished: data acquisition agents (sensor-based, laboratory, and exploration agents); preprocessing agents (filtering, correction, interpolation, normalization); analytical agents (geostatistics, modeling, forecasting); optimization agents (resource allocation, routing, regime modeling); control agents (process coordination, data integration, decision-making); and interface agents (visualization, reporting, human–system interaction). Each group of agents has its own operating protocols, levels of autonomy, and decision-making mechanisms. The conceptual model defines the rules and sequences of their interactions, ensuring data flow from the lower level (information acquisition) to higher-level analytical and control agents [1].

An important element of conceptual design is the selection of the architectural structure. Three main types of architectures are possible: centralized, hierarchical, and distributed. However, under geometallurgical conditions, a hybrid architecture that combines the advantages of all three approaches is considered the most effective. In a hybrid architecture, local agents possess a high degree of autonomy and can make decisions based on local information, while a supervisory layer provides global optimization and synchronization. This approach enables the system to adapt to changing conditions, minimize delays, and increase resilience to failures.

A key stage is the design of the communication model. This includes the definition of message types, request and response formats, mechanisms for synchronous and asynchronous data exchange, and routing methods. Most processes are characterized by asynchronous operation, in which agents can function independently, send notifications, respond to events, and initiate actions by other agents.

During the design process, particular attention is given to the robustness of communications against errors, delays, and interruptions. The system may incorporate mechanisms for message delivery confirmation, retransmission attempts, message queue storage, source reliability assessment, and ranking of communication channels.

Another essential component of the conceptual stage is the development of an adaptability and learning model for agents. Agents must be capable of updating their internal models based on new data, accounting for trends, detecting anomalies, and adjusting decision-making strategies. For example, an ore quality forecasting agent must adapt to changing geochemical conditions, while an optimization agent must respond to variations in production load or ore composition.

Thus, conceptual design of the multi-agent architecture is a critically important stage that forms the foundation of the entire intelligent digital geometallurgical system. It ensures data structure coherence, role distribution, the establishment of interaction mechanisms, and the creation of conditions for agent autonomy and learning. This stage determines the future flexibility, scalability, and overall effectiveness of the architecture, making it a key element of the methodology.

Methods for architecture evaluation and validation

The final stage of the methodology for designing an intelligent digital geometallurgical system is the development of methods for evaluating and validating the architecture. This stage determines the extent to which the designed system meets the requirements identified at earlier stages and whether it is capable of addressing real production challenges. Architectural evaluation encompasses a set of criteria, tests, simulation scenarios, and experimental studies that make it possible to assess computational efficiency, robustness, forecasting accuracy, scalability, and adaptability.

The first component of the evaluation is the analysis of computational efficiency. Multi-agent systems consist of numerous interacting components, and their performance depends not only on individual agents but also on the quality of communication among them. Metrics such as data processing speed, message latency, system response time, and the performance of individual machine learning models are assessed. Particular attention is paid to the system's ability to operate in real time. In the context of mining and metallurgical enterprises, where technological processes are continuous, the system must ensure responsiveness and timely decision-making. If latency exceeds a threshold value, the architecture is considered inefficient and requires refinement [2].

The next stage is the assessment of scalability. The architecture must maintain performance as the number of data sources increases, data volumes grow, and new modules and agents are introduced. Scalability is tested through scenario-based simulations that model workloads exceeding current production volumes, as well as the addition of new agents, changes in data arrival frequency, and increased complexity of predictive models. If the system demonstrates stable operation without significant increases in latency or error rates, the architecture is considered scalable.

An important aspect of the evaluation is the verification of the accuracy and reliability of analytical and predictive models. Validation is performed using test datasets, cross-validation, back-testing, and comparative analysis against benchmark solutions. The following characteristics are evaluated: forecasting accuracy, robustness to noise, anomaly detection capability, correctness of missing data handling, and model stability. These parameters are critical for geometallurgical systems, as errors in forecasting ore quality or technological parameters can lead to significant economic losses.

A separate evaluation block is associated with the architecture's robustness to uncertainty and failures. Scenarios involving missing data, noise distortions, equipment failures, and communication loss are tested. The system must demonstrate the ability to recover data, correct results, switch to safe operating modes, and notify supervisory agents of emerging issues. The presence of data quality control mechanisms and early warning systems increases architectural reliability and makes it more suitable for industrial deployment.

The final stage is the assessment of digital maturity. This analysis examines the extent to which the system improves information flows within the enterprise, reduces manual labor, accelerates decision-making, enhances reproducibility of analyses, and decreases the impact of the human factor. Digital maturity is evaluated based on KPIs such as increased forecasting accuracy, reduced production losses, shorter decision-making times, higher trust in data, and improved integration quality.

Thus, architecture evaluation and validation make it possible to determine whether the designed system meets established requirements and can operate effectively under complex geometallurgical conditions. This stage provides confidence in the correctness of decisions made during earlier design phases and forms the basis for deploying the intelligent digital geometallurgical system in a real production environment.

III.RESULT

Integration of multi-agent algorithms and digital twins in the conceptual model of the IDGMS

The conceptual model of a digital geometallurgical system based on multi-agent technologies is built on the principles of flexible integration of heterogeneous data, predictive analytics, and autonomous control. Unlike traditional multi-agent systems (MAS), this model places primary emphasis on close interaction between multi-agent algorithms and digital twins of key elements of the production chain, including ore deposits, crushing and grinding circuits, flotation units, and hydrometallurgical lines. In this context, digital twins serve as a continuous environment for testing agent strategies, assessing potential risks, and forecasting production scenarios [3].

Multi-agent algorithms in the conceptual model perform distributed data management, signal processing from sensor systems, and automated correction of digital twin models. Each agent is capable of autonomous decision-making within its domain of specialization, while simultaneously participating in collective decision-making through coordinated communication protocols. This approach enables the system to adapt to variable geological and technological conditions, forecast changes in valuable component grades, and minimize losses during processing stages [4].

The integration of digital twins provides the ability to perform scenario-based modeling of production processes. Agents analyze various scenarios—such as changes in ore quality, equipment failures, or shifts in grinding parameters—and automatically adjust the operation of related modules, forming adaptive production management plans. The conceptual model incorporates multi-level data processing: the operational level ensures immediate response to anomalies; the analytical level generates predictive models and scenarios; and the strategic level uses analytical results for long-term planning [5].

Special attention in the conceptual model is given to ontological knowledge management, where agents operate using unified terms and semantic relationships. This reduces the likelihood of errors in interpreting heterogeneous data and enhances system coherence. Ontologies include information on ore mineral composition, processing parameters, physicochemical properties of materials, equipment characteristics, and temporal aspects of processes. Such a knowledge structure enables contextual analysis of incoming data and supports adaptive routing of information flows, which is particularly important when handling large volumes of geological exploration and production data [6].

The conceptual model also integrates mechanisms for proactive monitoring and self-regulation. Agents continuously track key performance indicators, including processing throughput, pit block boundaries, mineral grades, and metallurgical stage efficiency. When potential deviations are detected, agents initiate corrective actions: adjusting crushing parameters, redirecting ore flows, modifying flotation regimes, and redistributing computational tasks among analytical modules. This approach ensures resilience to unforeseen changes and allows the system to maintain optimal metallurgical recovery rates [7].

Another key feature of the conceptual model is the integration of external data and digital services. Agents can connect to ERP and MES systems, the Industrial Internet of Things (IIoT), satellite monitoring systems, and geophysical databases, thereby expanding the decision-making context. The use of external sources enables adaptive resource management, market risk forecasting, consideration of environmental and regulatory constraints, and the generation of strategic production management recommendations.

The conceptual model also accounts for system scalability and extensibility. The architecture is modular, allowing the addition of new agent types—such as those for energy optimization, environmental monitoring, or transport logistics—without restructuring the entire system. Each new agent is automatically integrated into the digital ecosystem and adheres to established communication protocols and collective decision-making rules. This scalability ensures long-term relevance and future integration of advanced artificial intelligence technologies.

Thus, the conceptual model of a digital geometallurgical system using multi-agent technologies represents a highly adaptive, self-regulating architecture capable of effectively integrating multi-agent algorithms, digital twins, ontological models, and external data sources. This approach ensures coordinated agent actions, high forecasting accuracy, resilience to changing conditions, and the generation of strategic decisions aimed at optimizing production processes and improving the efficiency of the mining and metallurgical complex.

Modeling of forecasting and optimization processes using multi-agent strategies

The conceptual model of the digital geometallurgical system provides for active use of multi-agent strategies for forecasting technological processes and optimizing production performance. Unlike static models, the multi-agent architecture enables dynamic forecasting through the integration of sensor data, laboratory analyses, digital twins, and historical production indicators. Each agent performs a specialized function, such as forecasting valuable component grades in ore, evaluating mineral behavior during flotation, or optimizing ore flow distribution among processing plants. The integration of these functions forms a collective intelligent framework capable of self-correction and adaptive reconfiguration under highly variable geological and technological conditions.

Predictive agents employ machine learning methods, including ensemble algorithms, recurrent neural networks, and regression models, to analyze time series of technological parameters. Within the conceptual model, agents process not only current data but also forecast potential changes using scenario-based modeling that accounts for seasonal fluctuations, unforeseen technological events, and variations in raw material quality. This approach enables predictive control of crushing, grinding, flotation, and hydrometallurgical processes, allowing advance adjustment of equipment operating modes and resource redistribution across divisions.

Special emphasis is placed on collective decision-making mechanisms and coordination of predictive strategies. Since different agents pursue local objectives—ranging from maximizing metal recovery to minimizing energy consumption—protocols for action coordination and integration of predictive results are required. Distributed voting methods, coalition strategies, and hybrid auction-based algorithms are used to select optimal solutions that account for multiple conflicting criteria. These mechanisms enable agents to dynamically align their predictive models and form globally optimal system-wide operating strategies.

The model incorporates feedback loops between predictive agents and digital twins of production facilities, creating a continuous model improvement cycle. Equipment, sensor, and analytical system data are used to refine forecasts, update mathematical models, and adapt machine learning algorithms. This approach minimizes error accumulation in predictive assessments, improves forecast accuracy, and enhances the stability of technological processes.

For implementing optimization strategies, agents apply multi-objective algorithms that simultaneously minimize production costs, metal losses, and energy consumption while accounting for constraints related to production capacity, environmental indicators, and regulatory requirements. Optimization agents interact with analytical and predictive agents, forming iterative cycles of planning and operational adjustment. Multi-objective approaches enable the modeling of trade-off solutions and achievement of an optimal balance between economic efficiency, productivity, and process sustainability.

An important element of the conceptual model is adaptive routing of data and information flows between agents.

Predictive and optimization agents utilize flexible data transfer schemes, enabling redistribution of computational resources, prioritized access to critical information, and avoidance of communication bottlenecks. This mechanism is particularly important when multiple digital twins operate simultaneously and when large volumes of sensor and laboratory data are processed. Integration of data flows with consideration of latency and indicator importance allows the system to maintain coherence and high forecasting accuracy even under high data loads.

Another innovation of the conceptual model is the integration of external analytical services and global data sources to enhance forecasting quality. Agents can utilize geophysical and satellite data, market forecasts, meteorological information, andregulatory data to adjust their scenarios and optimization strategies. This integration allows the multi-agent system to consider not only internal technological factors but also external influences, increasing the adaptability and strategic robustness of the entire digital geometallurgical system.

Thus, this section describes conceptual approaches to modeling forecasting and optimization processes in a multi-agent digital geometallurgical system, emphasizing the importance of integrating predictive algorithms, digital twins, adaptive information flows, and collective decision-making mechanisms. The result is a highly adaptive, self-regulating system capable not only of predicting changes in technological processes but also of optimally adjusting them in real time, ensuring maximum efficiency of mining and metallurgical operations.

Integration of digital twins and production scenario management in a multi-agent system

The conceptual model of the digital geometallurgical system provides for the active use of digital twins as a key element in managing production scenarios and supporting operational decision-making. Within the multi-agent architecture, each digital twin represents a virtual counterpart of a real object—whether a pit block, a crushing unit, a flotation line, or an entire processing plant. Digital twins enable continuous modeling of physical processes, technological reactions, and material interactions, while agents interact with them to refine forecasts, optimize resources, and control product quality [8].

A key feature is the construction of a multi-scale network of digital twins, encompassing local, zonal, and global models. Local digital twins cover individual equipment units or specific processes, providing detailed parameter monitoring and immediate intervention capabilities. Zonal models integrate multiple local twins, forming an analytical framework for ore distribution, equipment load, and material flows at the level of individual plant sections. Global twins integrate data from all zonal models, enabling strategic management of the entire production chain and forecasting of aggregate indicators such as metal recovery, energy efficiency, and economic profitability.

The multi-agent system manages these digital twins through distributed algorithms that allow agents to analyze process states in real time, identify potential bottlenecks, and adjust operating scenarios for equipment and ore flows. Predictive analysis agents, together with optimization agents, generate “what-if” scenarios by modeling the consequences of changes in technological parameters, resource redistribution, or external factors such as fluctuations in ore grade or logistics conditions.

One of the innovations of the conceptual model is intelligent management of interactions between digital twins and the multi-agent network. Agents use adaptive communication protocols to exchange data on model states, predictive indicators, and deviations from planned values. The system continuously monitors key performance indicators (KPIs) and automatically initiates corrective actions—for example, retuning flotation regimes, redistributing crushing streams, or adjusting mining plans. This approach creates the effect of a “self-tuning plant,” where decisions are made with consideration of both local and global production parameters.

An important component of the model is data processing and synchronization between digital twins and external information sources, including geophysical data, satellite imagery, laboratory results, IIoT indicators, and ERP and MES systems. Digital twin agents analyze these data to generate corrective forecasts and refine mathematical models. This approach allows the system to account for both internal technological processes and external influences, increasing prediction accuracy and minimizing risks.

The conceptual model also supports real-time scenario analysis and optimization simulations. Agents generate alternative equipment operating scenarios and evaluate their impact on metal recovery, production costs, and environmental indicators. The model supports an iterative planning process in which scenarios are tested on digital twins, results are analyzed by optimization agents, and adjustments are made based on achieved outcomes. This cycle enables the identification of compromise solutions that balance economic efficiency, product quality, and process sustainability.

Another key aspect is the collective adaptation of agents to changes in both digital and physical environments. When anomalies are detected—such as sharp declines in ore grade, equipment overloads, or flotation parameter deviations—agents initiate coordinated actions to redistribute flows, modify operating modes, and update predictive models. Interaction between agents and digital twins ensures continuous coordination of actions and maintains system resilience under high loads and dynamic changes.

Thus, the integration of digital twins with a multi-agent system for production scenario management provides high adaptability, predictive control, and optimization across all levels of the production chain. As a result, an intelligent digital geometallurgical system is formed that is capable of dynamic self-regulation and ensures maximum efficiency and sustainability of technological processes.

Conceptual architecture of the multi-agent IDGMS

The conceptual architecture of the multi-agent IDGMS, presented in Figure 1 is organized as a three-level hierarchy integrated through a unified information and semantic data bus. This structure ensures coordinated operation of heterogeneous software agents under conditions of high variability in mineralogical and technological parameters, fragmented digital infrastructure, and the need to maintain continuous production processes in the mining and metallurgical complex.

At the upper level of the architecture, an integration data bus and a semantic layer are implemented, performing functions of format standardization, information flow routing, and ontological unification of geometallurgical concepts. The integration bus provides end-to-end data transmission between internal system agents, corporate information systems (ERP, MES, LIMS, SCADA), laboratory infrastructure, Industrial Internet of Things (IIoT) systems, and external contextual sources (geophysical and satellite data, regulatory information, market indicators, etc.). At this level, a geometallurgical ontology is implemented, including descriptions of mineral phases, technological stages, ore quality parameters, and production indicators. This ensures semantic interoperability of all agents and eliminates ambiguity in data interpretation during inter-subsystem data exchange.

The operational level is represented by a set of agents responsible for primary data acquisition, filtering, and calibration. These include sensor and IoT agents aggregating data from online ore composition analyzers, vibration and geomechanical sensors, and equipment telemetry; geospatial referencing agents ensuring synchronization of data with three-dimensional coordinates of orebody blocks and tracing of ore flows; laboratory agents integrating chemical and mineralogical analysis results; and technical condition monitoring agents recording operating modes of crushing and grinding equipment, pumping stations, and flotation machines.

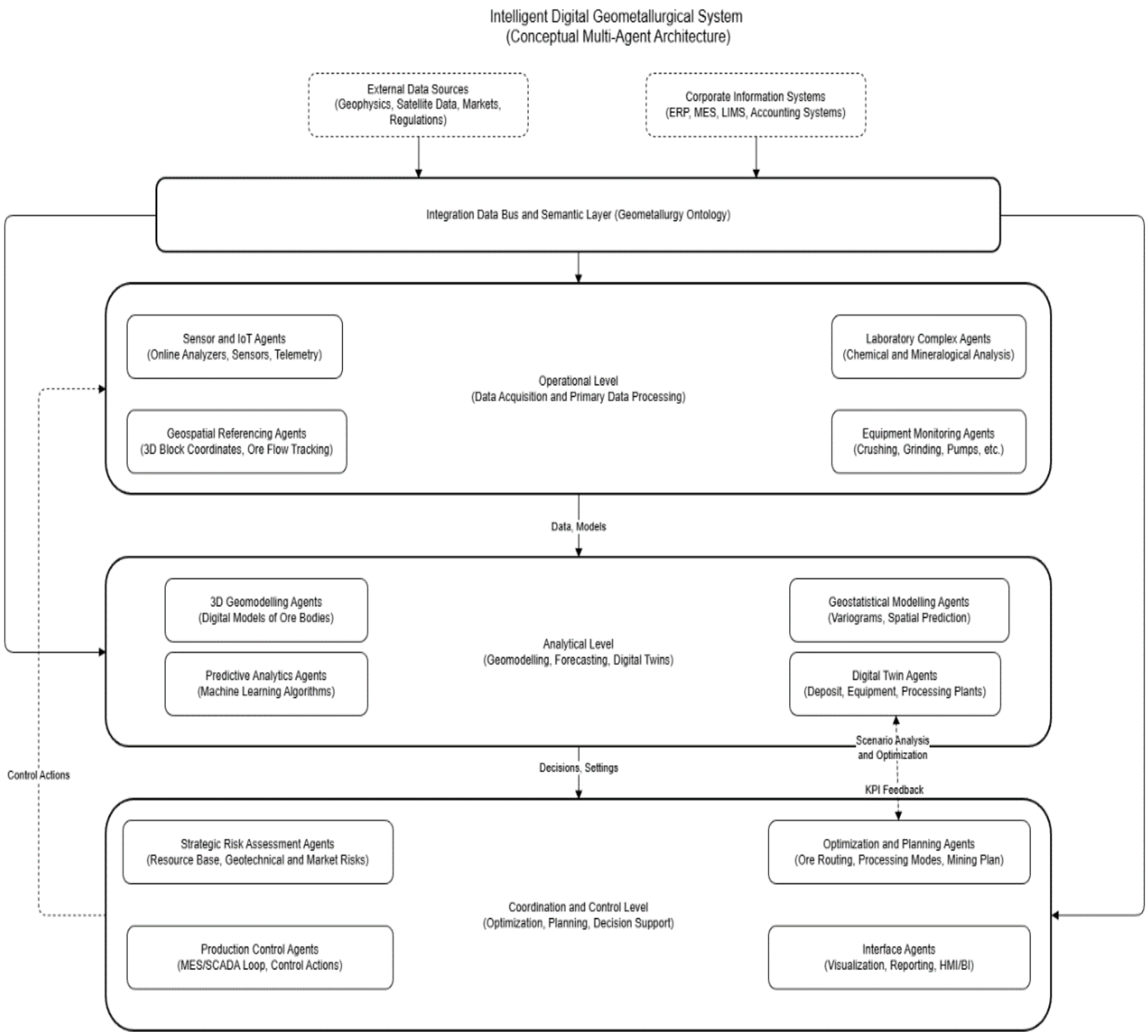

Figure 1 — Intelligent Digital Geometallurgical System (Conceptual Multi-Agent Architecture)

The operation of these agents is organized in a near-real-time mode, which requires minimal latency, robust message exchange, and the use of publish/subscribe protocols for selective and reliable delivery of relevant information to higher-level layers.

The analytical level concentrates on intelligent mechanisms for building digital geometallurgical models, forecasting, and evaluating production chain operation scenarios. The architecture includes geostatistical modeling agents that generate variogram models and spatial forecasts of valuable component distributions; three-dimensional geomodeling agents that construct digital models of ore bodies and structural–tectonic elements; predictive analytics agents using machine learning methods to analyze time series of technological parameters and forecast beneficiation process behavior; and digital twin agents implementing virtual models of deposits, individual units, and processing plants. These agents operate in close interaction with the integration bus, rely on unified ontological descriptions, and are capable of initiating dynamic model recalculation when anomalies are detected or when ore quality changes.

The coordination-control level ensures aggregation of analytical results, development of optimization and strategic decisions, and their translation into control actions applied to lower levels. This level includes optimization and planning agents solving problems of ore flow distribution between plants, selection of crushing, grinding, and flotation regimes, optimization of mining schedules and equipment utilization; strategic risk assessment agents analyzing the sustainability of the resource base as well as geotechnical, environmental, and market risks; production control agents integrated with MES/SCADA loops and generating specific control commands for technological objects; and interface agents responsible for visualization, reporting, and interaction with operators and engineering personnel. This level implements distributed decision-making functions based on multi-criteria optimization results and mechanisms for reconciling potentially conflicting objectives of various subsystems.

Inter-agent interaction is organized in a hybrid form combining direct and indirect communications. Direct communication uses standardized speech-act protocols compatible with FIPA ACL, providing formalized interpretation of message intentions (request, inform, propose, confirm, etc.) and enhancing reproducibility and transparency computational procedures. Indirect interaction is implemented through the integration bus and specialized coordinator agents responsible for message routing, data filtering, quality control, and queue management. Under conditions of high information flow intensity, this organization prevents network overload, message duplication, and inconsistencies during concurrent model updates.

A central feature of architecture is the inclusion of a network of digital twins distributed between the analytical and coordination-control levels. Local digital twins of equipment and technological chain segments provide detailed monitoring and enable rapid adjustment of operating modes, while global digital twins of the deposit and processing plant support strategic planning and assessment of overall performance indicators. Predictive analytics and optimization agents use digital twins as a computational environment for scenario-based ("what-if") modeling, evaluation of the consequences of process parameter changes, and assessment of the impact of equipment degradation or ore quality variability. This mechanism closes the loop "data – model – decision – control action – new data," enabling predictive and self-tuning management of geometallurgical processes.

The design of information flows within this architecture is based on the separation of operational, tactical, and strategic loops. Operational flows are formed at the operational level and are used for immediate adjustment of equipment and process-line operating modes. Tactical flows consolidate aggregated data and analytical model results to assess ore quality, ore behavior during beneficiation, and the selection of optimal processing routes. Strategic flows integrate long-term indicators of mining, processing, and product sales, as well as external contextual data, providing decision support for resource base management and digital transformation of the mining and metallurgical complex. The integration bus and ontological layer ensure end-to-end connectivity of these loops, multi-layer data validation, and architectural resilience to uncertainty and noise.

Thus, the proposed multi-agent architecture of the Intelligent Digital Geometallurgical System combines multi-level organization, ontology-driven data integration, the use of digital twins, and distributed optimization mechanisms. This enables not only detailed analysis and forecasting of geometallurgical process behavior, but also the formation of scientifically grounded strategic decisions aimed at increasing digital maturity and overall efficiency of the mining and metallurgical complex.

IV.DISCUSSION

Structural organization of the multi-agent architecture of the IDGMS

The structural organization of the multi-agent architecture of an intelligent digital geometallurgical system (IDGMS) represents a scalable, heterogeneous, and dynamic model that enables distributed decision-making under conditions of high variability in mineralogical and technological parameters of ore feed material, production conditions, and geological–industrial scenarios. The architectural approach is based on integrating multiple autonomous software agents capable of interacting with one another, processing large volumes of data, adapting to the emergence of new information sources, and supporting real-time operation of the digital model of the deposit and the production chain.

A key principle of the structural organization of the multi-agent system is a multi-level hierarchy. This hierarchy includes three main levels: operational, analytical, and coordination–control. Each level operates its own set of agents performing specialized tasks, while remaining fully integrated within the overall information exchange framework. Such an architecture ensures a balance between local agent autonomy and global coherence of system behavior, which is particularly critical in geometallurgy, where data are highly heterogeneous and technological processes are sensitive to even minor changes in raw material properties.

Operational level

The operational level includes agents responsible for primary data acquisition, filtering, calibration, and transmission. These include sensor agents receiving data from geophysical sensors, online ore composition analyzers, and vibration sensors on equipment; sampling agents integrating results of sampling campaigns; laboratory agents acquiring chemical and mineralogical analysis results; equipment monitoring agents tracking the condition of crushing, grinding, pumping units, and other assets; and geospatial alignment agents synchronizing data with 3D coordinates of the deposit, pit blocks, and ore streams.

These agents operate under conditions of high data update rates, requiring minimal latency and robust message exchange. Low-level communication protocols with minimal overhead are used to ensure rapid response and reliability under high-throughput conditions. Owing to the publish/subscribe architecture, operational agents transmit updates only to those components that explicitly request them [9].

Analytical level

The analytical level of the multi-agent architecture is responsible for intelligent data processing, in-depth analysis, and the construction of digital geometallurgical models. It includes geostatistical modeling agents that build variograms, identify spatial dependencies, and forecast the distribution of mineral phases; three-dimensional geomodeling agents that generate digital models of ore bodies; mineralogical and technological modeling agents that evaluate ore behavior in crushing, grinding, flotation, hydrometallurgical, and other processes; predictive analytics agents employing machine learning methods to forecast future process behavior; and digital twin agents modeling processing plants and production chains.

The proactive behavior of these agents is reflected in their ability to initiate model recalculation when anomalies are detected, such as increased variability in valuable component grades or changes in ore particle size distribution. Analytical agents rely on a unified geometallurgical ontology, ensuring a common terminological foundation and consistent interpretation of data across all subsystems.

Through the use of specialized optimization methods and intelligent coordinating agents, the analytical level can perform large-scale computations by distributing tasks across multiple subsystems. This enables high architectural flexibility and resilience to variability in the technological environment typical of mining and metallurgical operations.

Coordination-Control level

At the upper level, high-level intelligent agents operate, including ore routing optimization agents, mining planning agents, strategic risk assessment agents, technological flowsheet selection agents, and economic–metallurgical analysis agents. These agents generate decisions that determine changes in pit block boundaries, adjustments to blasting operations, redistribution of ore flows between plants, and selection of grinding and flotation regimes. Their activities are aimed at achieving global objectives, such as increasing metallurgical recovery, reducing production costs, minimizing risks, optimizing logistics, and ensuring sustainable development.

The system supports bidirectional information flows between layers: data move bottom-up—from observation to analysis and then to control—while control actions propagate top-down, synchronizing the behavior of all agents. As a result, the multi-agent architecture becomes capable of adaptation, self-correction, and predictive control.

The three-level structural organization promotes modularity and extensibility, allowing new types of agents to be added, existing ones to be upgraded, and advanced machine learning, data analytics, and modeling technologies to be integrated.

Organization of inter-agent interaction, communication protocols, and self-organization mechanisms

The organization of inter-agent interaction in an intelligent digital geometallurgical system is a fundamental principle that determines the integrity, robustness, and predictability of the entire architecture. Under conditions of high uncertainty inherent in geological and technological processes, agents must not only exchange data but also form shared interpretative frameworks, coordinated behavioral strategies, and adaptive mechanisms for collective decision-making. Geometallurgical processes—from variogram construction to the selection of optimal processing regimes—are characterized by high variability and multifactor complexity, which necessitates systemic methods for coordinating actions among heterogeneous computational and functional agents. Consequently, inter-agent interaction is not an auxiliary component but a core element of the intelligent architecture.

A key principle is the development of a hybrid communication model that balances direct and indirect agent interactions. Direct communications involve message exchange between agents without intermediary control nodes, significantly reducing latency, enabling rapid response, and maintaining data relevance in environments with intensive geoinformation updates. At the same time, indirect interaction through coordination services—such as knowledge-routing agents and coordinator agents—ensures structured communication flows, data filtering, and quality control of incoming messages. This approach prevents network overload, data duplication, and conflicts during model updates. International studies confirm that hybrid communication schemes provide optimal operating modes for multi-agent systems in complex industrial environments integrating thousands of heterogeneous objects [10].

Another important aspect is the standardization of interaction protocols. The architecture of the digital geometallurgical system employs speech-act protocols based on FIPA ACL standards, which define message structures, intent types, request handling mechanisms, and response behaviors. This ensures uniform interpretation of information by all agents—from geostatistical and mineralogical modeling agents to ore routing optimization agents and digital twins of processing lines. Standardized protocols reduce uncertainty in information exchange, prevent synchronization errors, and ensure reproducibility of computational processes under continuous change. Research in communication protocol engineering emphasizes that unification of speech acts is a key prerequisite for long-term sustainability and scalability of multi-agent systems [11].

Of particular importance is the development of decision coordination mechanisms among agents, as conflicts of interest between subsystems are inevitable in geometallurgical processes. For example, geological modeling agents may prioritize maximum structural model accuracy, while technological optimization agents aim to ensure processing stability and cost minimization. In such cases, multi-agent coordination mechanisms are applied, including negotiation protocols, distributed auctions, cooperative planning, behavioral contracts, and decentralized consensus methods. Auction-based protocols are especially effective for allocating limited resources such as equipment, time slots, laboratory analyzer capacity, and processing routes. Studies show that these mechanisms improve the efficiency of distributed decision-making, reduce conflict risks, and enable systems to achieve global objectives despite local contradictions among agents [12].

Self-organization mechanisms constitute one of the most critical components of the architecture, as they enable the system to maintain stability under both external and internal changes. Self-organization implies the ability of agents to modify their roles, adapt behavioral algorithms, reassign tasks, and dynamically restructure interaction patterns based on incoming data analysis. For example, when a sharp change in ore quality is detected, technological optimization agents automatically adjust grinding and flotation regimes, while analytical agents perform unscheduled recalculations of geological or mineralogical models. Under conditions of high raw material variability, such mechanisms prevent technological disruptions, reduce the risk of product quality loss, and ensure production continuity. Contemporary research on self-organizing systems confirms that the implementation of these mechanisms significantly enhances the flexibility, adaptability, and resilience of digital architectures operating in multi-component production environments [13].

An additional important aspect is the establishment of a resilient communication network that ensures continuity and reliability of data transmission. In industrial digital systems, particular emphasis is placed on message quality control, detection of data gaps and errors, recovery of corrupted information packets, and automatic switching to backup channels in the event of communication failures. Redundancy of communication channels and duplication of critical communication lines help prevent data loss, which is especially important when monitoring crushing and flotation parameters, equipment condition, and geomechanical characteristics of the rock mass. Research in industrial distributed computing systems highlights that communication reliability is one of the primary factors influencing the safety and stability of production systems, including mining and metallurgical complexes [14].

Thus, the organization of inter-agent interaction in an intelligent digital geometallurgical system establishes an integrated mechanism for knowledge exchange, action synchronization, and adaptive behavior, ensuring high architectural resilience, dynamic reconfiguration capability, and effective achievement of production objectives under highly variable geological and technological conditions.

Design of Information Flows, Digital Loops, and Data Integration

The design of information flows in a multi-agent intelligent digital geometallurgical system is a key stage in shaping the architecture, defining the internal logic of the entire digital ecosystem, the nature of agent interactions, data transmission methods, and rules for integrating analytical services. The geometallurgical environment is characterized by high complexity, as it encompasses multi-scale data: geological cross-sections, structural and tectonic models, mineralogical and petrographic characteristics, sampling results, technological indicators of crushing, grinding, and flotation, equipment operating parameters, environmental indicators, and production cycle management data. Studies on digital ecosystems emphasize that the quality of data flow design directly determines analytical effectiveness, predictive model accuracy, and the adaptive capacity of the entire system.

One of the central principles in developing digital loops is the creation of a unified end-to-end data infrastructure covering all stages of the production chain—from exploration to metallurgical processing. This approach involves forming a connected digital space in which data circulate continuously among agents without breaks or time lags. The end-to-end loop integrates primary exploration data, operational mining information, ore grade parameters, processing plant performance indicators, metallurgical processing results, and strategic data on resource base sustainability. Research shows that the use of end-to-end data loops significantly improves the accuracy of predictive models and ensures synchronization of decisions across technological stages [15].

The design of information flows involves their classification into operational, tactical, and strategic flows. Operational flows include real-time data such as crusher sensor readings, mill load levels, flotation machine parameters, vibration characteristics, temperature, and pressure. Based on these flows, equipment control agents, digital twin agents, and process monitoring agents make immediate decisions to adjust operating regimes. Tactical flows encompass data processed over intervals ranging from minutes to hours, forming the analytical basis for grade assessment, ore quality determination at plant feed, selection of optimal processing routes, and analysis of ore body behavior. Strategic flows include long-term indicators required for mine planning, risk assessment, sustainability modeling, and strategic resource management. The multi-layer organization of flows enables the system to adapt to different temporal scales of processes, as confirmed by research in industrial digital system architecture [16].

A key design element is the development of a unified semantic data model and an industry-specific ontology of geometallurgical processes. The semantic model defines data structures, establishes semantic relationships between objects (geological blocks, minerals, technological parameters, production events), specifies interpretation rules, and standardizes information exchange formats among agents. This is particularly important when integrating data from dozens of sources, including borehole databases, industrial IoT systems, laboratory complexes, and ERP and MES platforms. Research in ontological modeling emphasizes that such models are mandatory components of complex digital platforms supporting multi-user and multi-agent data operations.

Information flow design also includes the implementation of data quality control, validation, noise processing, and error correction mechanisms. In geometallurgical systems, these tasks are critical, as errors in geological models may lead to incorrect reserve estimation, while erroneous flotation parameters can reduce metal recovery. Validation mechanisms include automated filtering of anomalous values, threshold configuration, intelligent outlier detection, reconciliation of technological parameters with predictive models, and cross-validation of data among agents. Studies indicate that systems lacking built-in multi-level validation exhibit low robustness and are prone to cumulative data errors.

A central role in the information architecture is played by the data integration bus, which provides flow routing, format transformation, message standardization, and information security. The integration bus connects all MAS modules—geological agents, equipment monitoring agents, modeling agents, predictive analytics agents, optimization agents, production management agents, digital twins, and visualization and reporting systems. Contemporary research notes that the integration bus determines the resilience of digital platforms and enables scalability to new modules without restructuring the entire architecture.

An important aspect is the provision of bidirectional data flows: bottom-up (data from equipment, sensors, and laboratories) and top-down (control actions, regime adjustments, mining assignments, optimization decisions). This scheme ensures cyclic operation of the digital loop: data are transformed into knowledge, knowledge into managerial decisions, and decisions into changes in technological object behavior. Researchers emphasize that this cyclicality is what imparts intelligence to industrial systems and enables the creation of self-tuning digital ecosystems [17].

Special attention is given to the design of data flows for digital twins. Digital twins of deposits, crushing equipment, mills, flotation units, or entire plants require continuous synchronization between actual and modeled data. Information flows must include equipment operating parameters, ore quality indicators, geometallurgical characteristics, and analytical model outputs. Such synchronization ensures predictive system behavior and enables agents to forecast risks and prevent failures.

The design of information flows also encompasses mechanisms for integrating external data, including satellite monitoring, remote sensing data, geophysical surveys, regulatory requirements, environmental metrics, market forecasts, and financial indicators. These data form the contextual basis for strategic decisions and enable the system to respond not only to internal but also to external factors. Contemporary studies highlight that the integration of contextual data improves scenario modeling accuracy and enhances long-term resource base management [18].

Thus, the design of information flows, digital loops, and data integration forms the foundation of an intelligent geometallurgical system. The quality of these mechanisms directly affects model accuracy, coherence of agent actions, robustness of production processes, and the system's ability to adapt to changes in geological and technological conditions.

V.CONCLUSION

This paper presents a conceptual framework for an Intelligent Digital Geometallurgical System (IDGMS) based on multi-agent technologies and digital twins, designed to address the complexity and variability inherent in modern mining and metallurgical operations. The proposed multi-level architecture integrates operational, analytical, and coordination-control levels through a unified information and semantic data bus, ensuring seamless data flow, semantic consistency, and adaptive decision-making.

By combining predictive modeling, geostatistical analysis, digital twins, and ontology-driven knowledge management, the system enables real-time monitoring, scenario simulation, and optimization of geometallurgical processes. Multi-agent algorithms provide distributed data processing, autonomous decision-making, and collective coordination, while digital twins offer a virtual environment for "what-if" analysis and continuous refinement of operational strategies. This integration allows the IDGMS to respond dynamically to changing ore characteristics, technological parameters, and production conditions, improving accuracy, efficiency, and sustainability.

The conceptual design demonstrates that multi-agent IDGMS can enhance geometallurgical modeling, optimize resource allocation, and support strategic decision-making, providing a robust foundation for increasing the digital maturity and operational performance of mining and metallurgical enterprises. Future work will focus on system implementation, real-world validation, and the integration of advanced AI algorithms for enhanced predictive capabilities and autonomous process optimization.

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