Multiagent System for Discrete Manufacturing with Integration into the MES/SCADA System and Production Decision Support

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Discrete manufacturing faces significant challenges related to high variability, mass customization, and the demand for rapid responses to operational failures, which increase costs and compromise process efficiency. Industry 4.0 emerges as a response to this scenario by promoting digitalization and intelligent system integration, enabling real-time monitoring and dynamic adaptation of production. The integration between the Manufacturing Execution System (MES) and Multi-Agent Systems (MAS) becomes essential to optimize processes, enable greater decision-making autonomy, and increase the resilience of the production system. This work proposes a multi-agent approach to optimize production in discrete manufacturing environments, integrating with MES/SCADA systems and establishing the foundations for a Digital Twin with Artificial Intelligence (AI) capabilities. The methodology was applied at the Advanced Manufacturing Plant (PMA) of SENAI CIMATEC, a demonstrative Industry 4.0 environment. The initial steps involve defining the agents, modeling the system, and integrating with MES, using a Service-Oriented Architecture (SOA) to expose functionalities as microservices. The results include the mapping and classification of PMA components, as well as the proposal of a preliminary agent structure, modeled in UML and divided into two groups: Device Agents, responsible for field data collection, and Management and Analysis Agents. It is expected that the Analyzer Agent will play a key role in detecting deviations or potential failures in the process by employing AI to predict faults and suggest rescheduling. The proposed solution offers a conceptual basis that integrates traditional technologies and intelligent agents to build an AI-enabled Digital Twin, capable of supporting dynamic rescheduling and adaptive control, enhancing responsiveness to changes and unforeseen events.
Keywords: Multiagent System. Discrete Manufacturing. MES. Industry 4.0.
Abbreviations: MES, Manufacturing Execution System. SCADA, Supervisory Control and Data Acquisition. MAS, Multi-Agent System. DT, Digital Twin. PMA, Advanced Manufacturing Plant. IIoT, Industrial Internet of Things. CNC, Computer Numerical Control. MTBF, Mean Time Between Failures. OEE, Overall Equipment Effectiveness. UML, Unified Modeling Language. HMIs Human-Machine Interfaces. M2M, Machine-to-Machine.

Discrete manufacturing faces growing challenges, such as high variability, mass customization, and demand for personalized products in small batches. These factors increase the complexity of production processes, requiring efficient coordination of real-time information. The absence of systems capable of anticipating failures and responding quickly to operational disruptions results in unplanned downtime and high costs [1].

Industry 4.0 emerges as a response to the limitations of traditional models, promoting the digitization of manufacturing and intelligent integration between machines, processes, and systems [2]. In this context, technologies continuously connect the physical and digital worlds, enabling real-time monitoring, predictive analytics, and operational simulations. This digital layer, coupled with productive assets, allows for dynamic adjustments and more agile decisions, making processes more responsive and efficient [3].

The integration of the Manufacturing Execution System (MES) with this digital infrastructure and Multiagent Systems (MAS) is fundamental to smart manufacturing. MES, traditionally responsible for mediating planning and operations, expands its role by incorporating updated production data, now also acting in the control and optimization of processes [4]. This synergy allows for quick reactions to events in real time, adjusting flows and priorities autonomously and contextually.

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With the addition of MAS, the architecture gains autonomy and adaptability. Distributed agents collaborate in resource allocation, fault management, and production reconfiguration in the face of variations or disturbances. This decentralized approach favors local decisions aligned with global objectives, promoting a more resilient, flexible production environment capable of responding quickly to the demands of mass customization and the uncertainties of industrial operation [5].

This paper aims to answer the following question: How can an MAS be designed to optimize discrete manufacturing, considering integration with MES/SCADA systems?

It is proposed to develop a MAS for discrete manufacturing, integrated with MES/SCADA systems, aiming to establish the foundation for the development of a Digital Twin (DT) with Artificial Intelligence (AI) capabilities, able to support autonomous decision-making for rescheduling and adaptive production control.

Related Works (Art Study)

In the study conducted by Nie and colleagues [1], a decentralized resilient scheduling method for flexible workshops is presented, structured in three hierarchical levels: shop floor, service unit, and machine. Each agent responds locally to disturbances using buffers, excess capacity, or lead time, and adopts a collaborative adaptive decision-making mechanism to enhance the system's resilience and efficiency.

Siatras and colleagues [4] demonstrates the use of a MAS for decentralized production scheduling in the bicycle industry. Agents manage task allocation in segments such as painting and assembly, in conjunction with DT and Asset Administration Shells, enabling flexible, parallel, and coordinated decisions to avoid bottlenecks and optimize performance.

Garcia, Oregui, and Ojer [6] proposes a framework with a MAS distributed between cloud and edge for collaborative production control. The use of DT and Industrial Internet of Things (IIoT) enables real-time data collection, optimizing resource allocation and supporting self-adaptive decisions in complex and dynamic production environments.

The systematic review presented by Kalyani and Collier [7] highlights the importance of MAS in the implementation of DT. Agents provide autonomy, scalability, and intelligence to DT, supporting decision-making, simulation, and operational efficiency, especially in manufacturing contexts.

In the work of Lyozin and Berger [8], a MAS is applied with DT for modeling production processes, aiming to reduce inefficiencies, downtime, and resource waste. The proposed approach allows dynamic rescheduling of only the affected part of the production and adopts an integrated classification function to maximize efficiency.

Kim and colleagues [9] proposed the integration of a MAS with reinforcement learning to create an intelligent manufacturing system. Machines with autonomous agents learn and make adaptive decisions through distributed negotiation, focusing on task prioritization and continuous performance improvement.

In Nie and colleagues [10], the MAS is applied for optimized manufacturing control, focusing on reconfiguration and agile response of the smart shop floor via DT. Agents represent people, equipment, and materials, enabling communication and autonomous decisions.

The analyzed studies present relevant advances in MAS for intelligent manufacturing. They cover resilient scheduling, collaborative control with DT and IIoT, decentralized scheduling, and the use of reinforcement learning. Despite this, the studies still show limited exploration of direct integration with management systems. This article proposes a MAS that architecturally integrates MES/SCADA systems. The proposal presents a conceptual foundation that promotes cooperation between traditional systems and autonomous agents and aims to build a digital twin with AI to support rescheduling and adaptive production control.

Materials and Methods

For the development of the proposed MAS, the Advanced Manufacturing Plant (PMA), located at SENAI CIMATEC in Salvador/BA, was selected. It is a pilot Industry 4.0 manufacturing plant with a didactic and demonstrative purpose. This environment is a scaled-down representation of industrial operations, with one of its objectives being to serve as a laboratory and testing space for the validation of methods, architectures, and emerging technologies in the context of Industry 4.0.

The PMA allows investigation and validation of intelligent management methods applied to customized production in flexible assembly lines, as well as illustrating the organizational capacity of cyber-physical systems in complex industrial environments. Focusing on the manufacturing and operation of processes related to finishing components such as covers and bases of pneumatic cylinders, the PMA integrates CNC machines and other automated stations to compose realistic industrial scenarios.

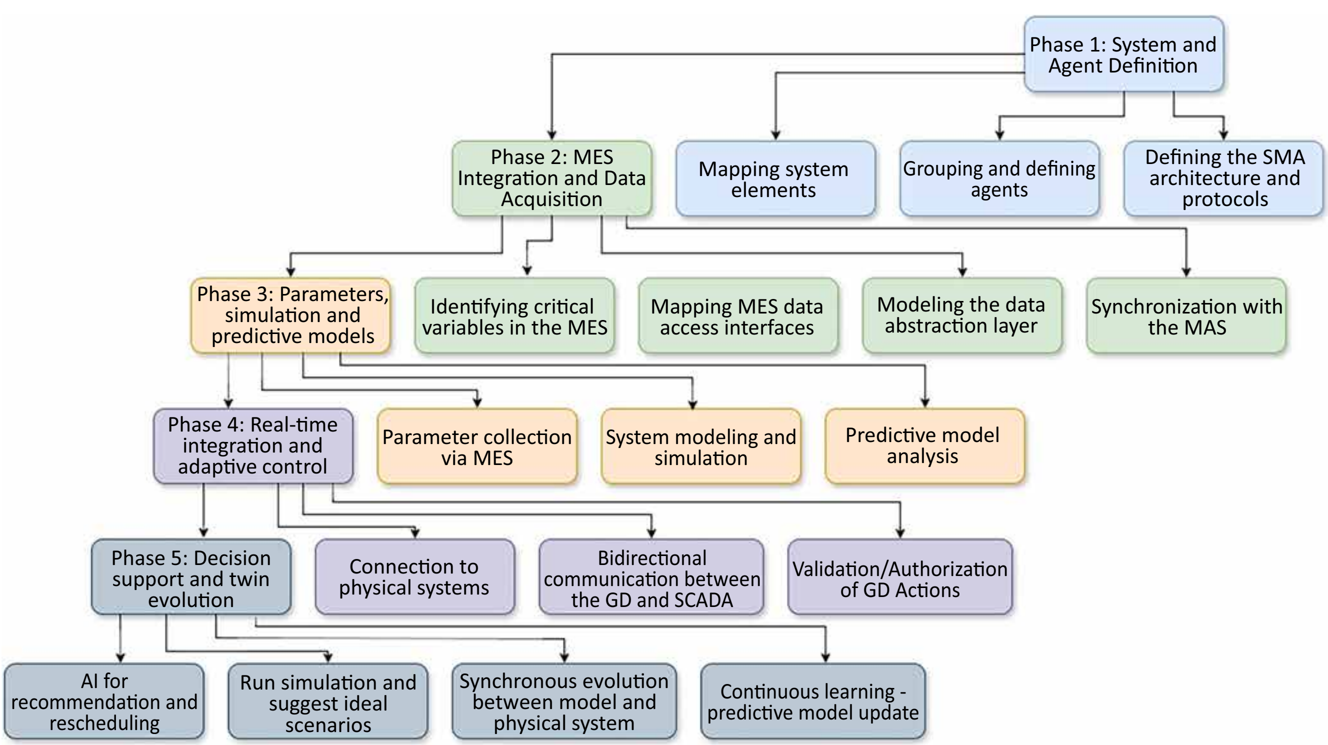
Based on a detailed analysis of the PMA production processes, a methodological framework was developed, illustrated in the flowchart in Figure 1. Phase 1 is dedicated to defining the system and agents, and Phase 2 focuses on integration with the MES for acquiring essential data.

The subsequent stages, from Phase 3 to 5, encompass modeling and predictive simulation, real-time integration, and adaptive control, resulting in decision support and continuous evolution of the digital twin. These stages will be addressed in future work.

System and Agentes Definition

In the first phase, the process for which the MAS will be developed is defined. In this work, the system is developed to manage a flexible assembly line aimed at producing customized items, based on the SAMOM model proposed by Cruz and Lepikson [11].

Figure 1. Methodological flowchart of the system for manufacturing with MES/SCADA integration.



Source: Author's own.

This stage requires detailed identification of physical and logical components, which will be abstracted as autonomous computational entities. Machines, workstations, products, operators, sensors, and production orders are mapped according to their function and level of abstraction: machines and workstations are grouped as productive resources, products and orders as flow entities, and operators and sensors as human and perception interfaces.

Each element is translated into an agent with well-defined roles in the system. These agents are specified according to their roles and responsibilities in the production cycle, their perception and action capabilities, and the types of information they must share.

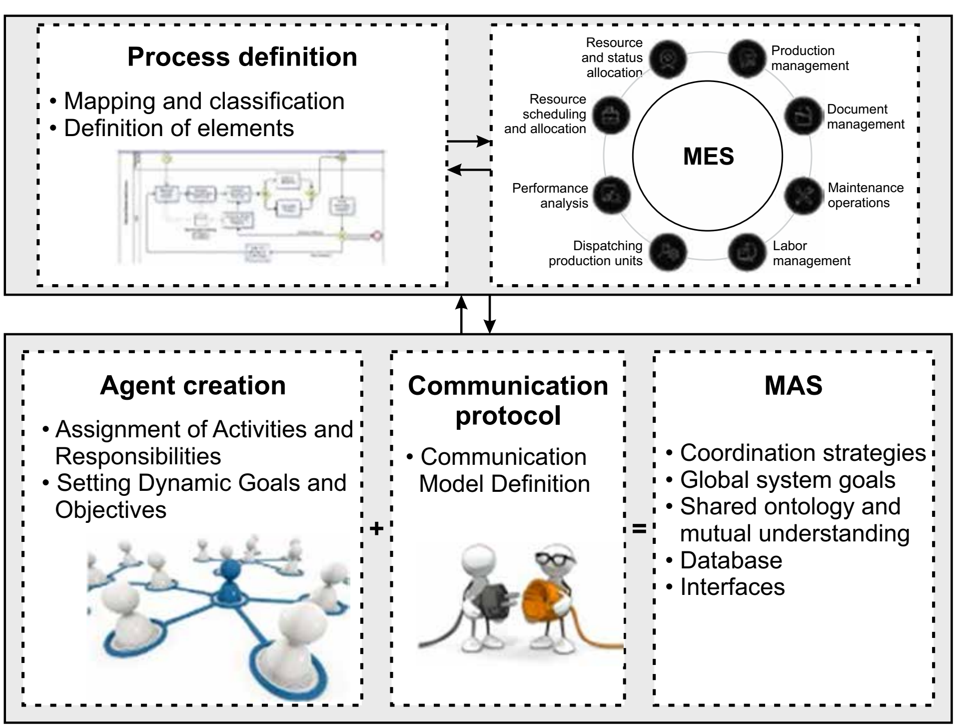
Agents are defined as computational elements capable of performing three main functions: perception (receiving signals and data), processing (executing calculations, logic, and inferences), and action (sending new signals and data). Another important principle is autonomy and negotiation among agents. Each agent can act and decide independently, interacting with other agents through negotiations to achieve its objectives.

MES Integration and Data Acquisition

The proposed integration between MES, SCADA, and MAS aims to establish a collaborative and adaptive architecture guided by Industry 4.0 principles, as described in Figure 2. The model starts from the understanding that for effective operation of autonomous agents, structured and real-time access to data generated by MES is essential, organized into critical categories reflecting the state of production, resources, and quality. To enable agents to make informed decisions, it is crucial to identify which MES data points are critical.

Among the main data points that must be monitored are: production scheduling and dispatch of production units; work-in-progress control and product tracking; status and allocation of machines, operators, and resources; material availability and inventory control; quality data of processes and products; and continuous performance monitoring

Figure 2. Representation of the integration between MES and MAS.



Source: Adapted from Tanajura, Lepikson and Freires [12].

based on key performance indicators (KPIs), such as cycle time, rework rate, takt time, Mean Time Between Failures (MTBF), and Overall Equipment Effectiveness (OEE) [13].

The modeling and access to this data are structured through a Service-Oriented Architecture (SOA) approach, in which MES functionalities (including services routed via SCADA) are provided as microservices consumable by agents. SCADA collects field signals by exposing services that both feed the MES and can be accessed directly by agents for low-latency operations.

The MES consolidates histories, processes KPIs (availability, takt time, output rate, cost, and quality), and provides its own microservices to the agent layer, which, decoupled from physical specifics by an abstraction layer in UML, can operate as reactive (simple data collection) or cognitive (AI/ML).

Expected Results

The components of the PMA were mapped and classified so that the agent structure to be implemented includes several functional classes that interact with each other to make production smarter and more adaptive. These agents were organized into two main groups: Device Agents, which represent the physical elements of the shop floor, and Management and Analysis Agents, which operate at higher levels of decision-making.

The modeling of agents was conducted using UML diagrams to represent their functions, interactions, and hierarchical relationships. A preliminary structural view of the agents is proposed, identifying only the main classes without detailing specific methods and attributes. Figure 3 illustrates this proposed organization of agents in the MAS, highlighting the planned types and their general relationships within the architecture.

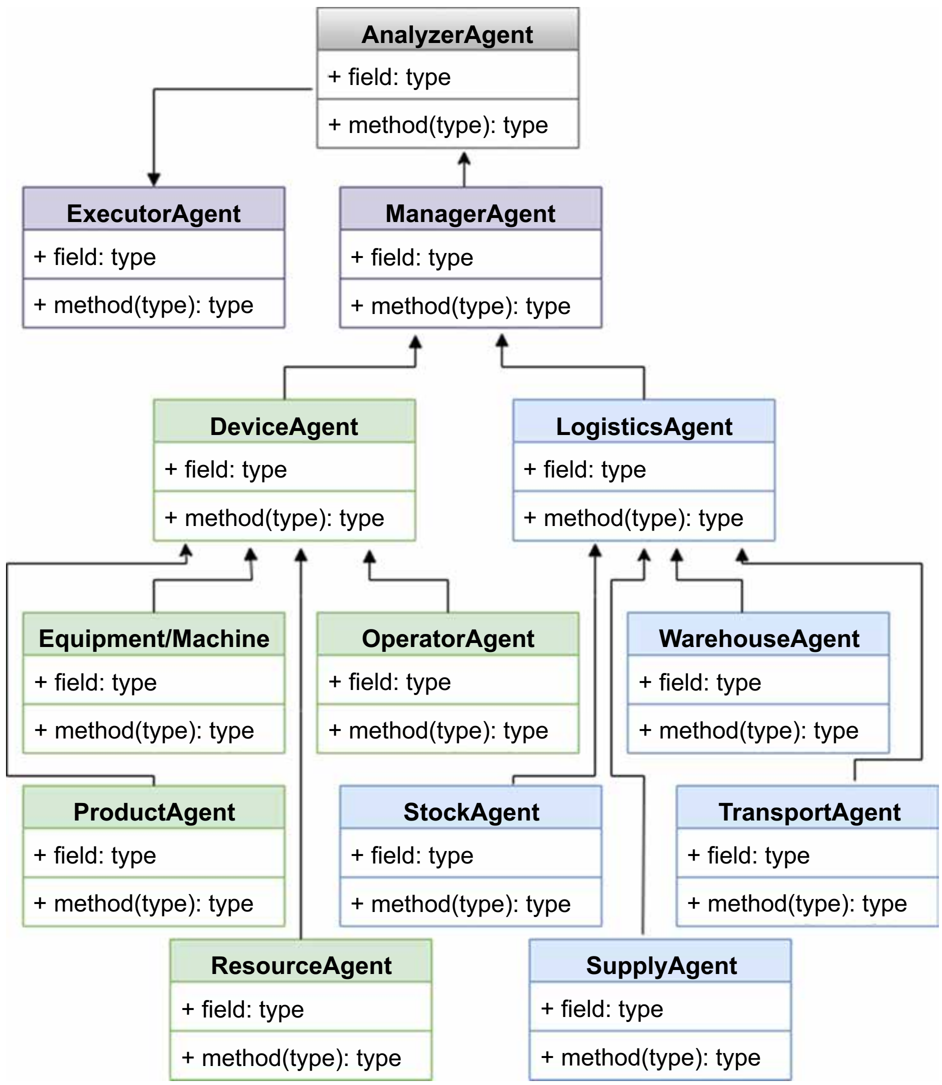
Device Agents are responsible for digitally representing the physical components of the factory and form the basis for the DT. Among them, the Equipment/Machine Agent stands out, which collects data from sensors, reports the machine's status (such as available, operating, or in fault), and also receives commands to change its operation. The Operator Agent represents human operators and is responsible for interacting with HMIs (Human-Machine Interfaces), providing information about their activities and availability. The Product Agent follows the product during its manufacturing, recording its current state, location, and the processes it has undergone. Finally, the Resource Agent is responsible for digitally representing the inputs and utilities used during the production process, such as compressed air, electrical power, and raw materials.

Management and Analysis Agents operate at a higher level, bringing intelligence to the system. The Analyzer Agent, for example, functions as the 'brain' of the operation. It receives data from Device Agents, the Logistics Agent, and the MES, and analyzes production scenarios. This agent is expected to use AI techniques to predict failures and propose rescheduling solutions. The Executor Agent comes into action after decision-making, being responsible for transforming the Analyzer Agent's recommendations into concrete commands sent to the Device Agents. It also monitors the execution of actions to ensure everything proceeds as planned. The Manager Agent can make decisions based on information from other agents. Its scope may involve a specific workstation or even a complete line, acting as a mediator between the Analyzer Agent and the other agents.

Communication among all these agents follows a service-oriented architecture (SOA) logic, enabling flexibility and integration. Within this flow, MES and SCADA play fundamental roles. Device Agents are the first to collect data directly from the shop floor, such as status, availability, and performance information, passing these data to the Manager Agent. MES provides important operational data, such as production orders, performance indicators, and process history. SCADA, in turn, complements this communication by providing real-time monitoring and control data.

Based on this data, the Analyzer Agent is expected to play a vital role in detecting deviations or potential failures in the process. From this perspective, AI

Figure 3. UML diagram of the organization of agents in the MAS.



models are intended to be employed to predict system behavior and simulate different production rescheduling alternatives, aiming to mitigate impacts. During the simulation, 'negotiations' may occur between agents, such as the Analyzer Agent consulting the Device Agent about its availability or the Logistics Agent about material supply. Based on these interactions, the Analyzer Agent selects and proposes the best possible scenario, considering criteria such as lowest cost or minimal downtime.

After the best alternative is defined, the Analyzer Agent sends this rescheduling proposal to SCADA. This proposal is then presented to the human operator, who must validate it. Approval by the operator acts as a trigger to activate the Executor Agent. After this validation, the Executor Agent sends the new commands to the Device Agents, which in turn pass these instructions to the physical equipment.

Interaction among agents occurs through cooperation, negotiation, competition, and coordination. For interoperability, the model uses M2M for direct communication, OPC UA for industrial integration, and Web Services (REST APIs with HTTP and JSON) for data exchange with MES. Technologies such as WebSocket, XML, and FIPA-ACL will also be considered. Alternative protocols (MTConnect, MQTT) and legacy ones (Modbus, OPC Classic) may be used occasionally.

Each agent recognizes the context and priority, coordinating with the MES or acting autonomously to avoid redundancy. This architecture aims for efficient, safe, and adaptive manufacturing operations, compatible with Industry 4.0, DT, and intelligent automation.

The synchronization of SCADA, MES, and MAS thus ensures fidelity and agility in communication between the physical world and its digital representation. Figure 4 demonstrates this integration with the PMA.

Conclusion

This work presents a MAS approach to optimize discrete manufacturing through a collaborative and adaptive architecture. The proposal structurally integrates MES/SCADA systems, bringing production control closer to the distributed intelligence provided by autonomous agents. The literature review revealed that direct integration between management systems and MAS is still underexplored.

The proposed solution establishes a conceptual foundation that combines traditional technologies and intelligent agents, with the goal of building a Digital Twin equipped with AI capabilities to support dynamic rescheduling and adaptive production control, enhancing responsiveness to changes and unforeseen events.

For future work, the modeling of the MAS is expected to continue, with an emphasis on Phases 3 to 5, focusing efforts on the development of the DT.

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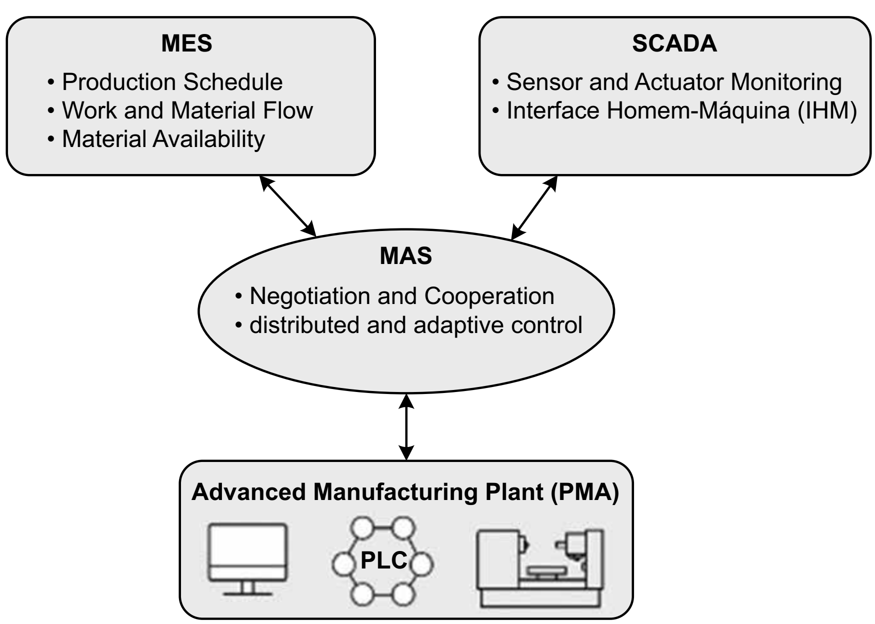
Figure 4. Integration between MES, SCADA, MAS, and the Advanced Manufacturing Plant (PMA).



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