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RESEARCH ARTICLE **OPEN ACCESS**

AUTOMATED CONTROL AND PLANNING SYSTEM FOR THE PRODUCTION OF ELECTRONIC METERS WITH ARTIFICIAL INTELLIGENCE

Jandecy Cabral Leite[1], Marcelo Maia do Nascimento[2], Marivan Silva Gomes[3], Alan Ferreira Pinheiro Tavares[4], André Barbosa de Lima[5], Matheus Pereira de Souza[6], Daniel Gomes Gulart[7] and Marcos Castro de Menezes[8]

[1, 2,3,4,5,6]Department of Industrial Research Department of the Galileo Institute of Technology and Education of Amazonia (ITEGAM). Address: Joaquim Nabuco, No. 1950. Neighborhood: Downtown. ZIP CODE: 69020-030. Manaus-Amazonas, Brazil.
[7,8]Wasion da Amazônia Electronic Instruments Industry LTDA. Av. Cosme Ferreira, No. 12.110. Colônia Antônio Aleixo. ZIP CODE: 69008-310. Manaus – Amazonas, Brazil.

[1]https://orcid.org/0000-0002-1337-3549, [2]http://orcid.org/0000-0001-7183-8642, [3]http://orcid.org/0009-0007-2022-9047
[4]http://orcid.org/ 0000-0003-1644-9999, [5]http://orcid.org/0009-0002-6910-0635, [6]http://orcid.org/0009-0008-3447-3566
[7]http://orcid.org/0009-0002-2787-7753, [8]http://orcid.org/0009-0000-7874-9132

Email: *jandecy.cabral@itegam.org.br, marcelo.nascimento@itegam.org.br, msgomes@uea.edu.br, alan.tavares@itegam.org.br, amilandre@gmail.com, matheus@itegam.org.br, daniel.gulart@wasion.com.br, marcos.castro.menezes@gmail.com

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ABSTRACT

In the context of Industry 4.0, modern manufacturing environments increasingly rely on digital technologies to enhance efficiency and competitiveness. The production of electronic meters represents a complex industrial process that demands precise coordination of resources, materials, and scheduling. Traditional methods of production planning often face challenges such as bottlenecks, resource underutilization, and delayed delivery times. To address these issues, the integration of Artificial Intelligence (AI) into manufacturing processes has emerged as a promising solution. The main objective of this research is to develop an automated system for production planning of electronic meters that leverages AI techniques to optimize operational performance. The study proposes a model capable of analyzing historical production data, predicting demand fluctuations, and dynamically adjusting production schedules. The methodology involves the implementation of machine learning algorithms and optimization techniques within a simulated industrial environment. The system evaluates different production scenarios, prioritizes tasks, and allocates resources efficiently to meet production targets while minimizing delays. Results demonstrate that the proposed AI-based automated system significantly improves operational optimization. Key performance indicators, such as production throughput, resource utilization, and lead time, showed measurable enhancements compared to conventional planning methods. Moreover, the system enables real-time decision-making, which aligns with the principles of Industry 4.0 and supports adaptive, data-driven production strategies. In conclusion, the research highlights the potential of combining Artificial Intelligence and automated systems to advance production planning for electronic meters, contributing to more efficient, flexible, and responsive manufacturing processes in the Industry 4.0 era.

I. INTRODUCTION

The rapid technological evolution of the industrial sector has accelerated the transition toward Industry 4.0, a paradigm characterized by digital integration, cyber-physical systems, data analytics, and intelligent automation.

In this new industrial landscape, manufacturing processes increasingly depend on advanced computational tools capable of enhancing efficiency, adaptability, and connectivity. The production of electronic meters, in particular, has faced growing challenges due to market expansion, demand variability, and the need for continuous improvement in quality and delivery performance. Traditional methods of Production Planning and Control often prove insufficient to handle the complexity of modern manufacturing environments, leading to inefficiencies such as delays, resource imbalances, and limited responsiveness to unforeseen changes [1-5]. To address these limitations, the introduction of Artificial Intelligence (AI) has emerged as one of the most transformative innovations in industrial operations. AI techniques—especially machine learning, optimization algorithms, and predictive analytics—offer the ability to process large volumes of data, identify patterns, and support decision-making with greater accuracy and speed. When applied to Production Planning and Control, AI enables systems to dynamically adjust schedules, predict bottlenecks, and optimize resource allocation in real time.

This creates a foundation for intelligent, flexible, and highly efficient manufacturing systems. In this context, the development of an automated system designed to enhance production strategies for electronic meters becomes essential. By integrating AI algorithms with industrial data streams, such a system can significantly contribute to operational optimization, reducing lead times, increasing production throughput, and minimizing waste. Furthermore, automation allows organizations to adapt more effectively to fluctuations in demand and operational disturbances, strengthening competitiveness in a globalized market [6-9]. Overall, the incorporation of Industry 4.0 concepts—combined with Artificial Intelligence and automated decision-making—marks a critical step toward transforming production environments. The application of these technologies to the manufacturing of electronic meters not only supports smarter Production Planning and Control but also aligns industrial processes with the current demands for agility, precision, and sustainability. This introduction lays the groundwork for exploring how intelligent systems can enhance industrial performance and redefine the future of automated production.

II. LITERATURE REVIEW

II.1 INDUSTRY 4.0

Industry 4.0 represents the fourth industrial revolution and is characterized by the deep integration of digital technologies, physical systems, and intelligent production processes. It emerged in response to the growing need for efficiency, customization, speed, and flexibility in modern manufacturing chains. Unlike previous revolutions, Industry 4.0 promotes the convergence of advanced automation, data analytics, interconnectivity, and computational intelligence, transforming traditional factories into fully connected and autonomous environments [10],[11]. Among its main characteristics is the adoption of cyber-physical systems capable of monitoring and controlling industrial processes in real time. These systems communicate with each other through the Internet of Things (IoT), allowing machines, sensors, and software to continuously exchange information. This connectivity creates a more transparent, efficient, and predictable production network. In addition, the use of Big Data and advanced analytics makes it possible to interpret large volumes of data generated during production, supporting strategic and operational decisions with greater accuracy. Within this ecosystem, Artificial Intelligence (AI) plays a central role. AI enables machines to learn patterns, predict failures, optimize routines, and make autonomous decisions. In industrial processes, machine learning algorithms assist in production planning, predictive maintenance, automated quality inspection, and performance analysis. AI also helps dynamically adjust production lines, reducing waste, increasing productivity, and ensuring greater reliability of results [12-15]. Another important characteristic of Industry 4.0 is horizontal and vertical integration. Horizontal integration connects different companies along the production chain, while vertical integration connects all levels of the organization—from the shop floor to corporate management. This integration ensures greater synchronization and efficiency. Thus, Industry 4.0 represents a transformative milestone, driving smart factories, data-driven decision-making, and a more flexible, sustainable, and competitive production model.

II.2 ARTIFICIAL INTELLIGENCE (AI)

Artificial Intelligence (AI) has established itself as a central element in modern technological advancement, especially when combined with other tools that make up the digital transformation ecosystem. Among these tools, the Internet of Things (IoT), Big Data, Machine Learning, and several techniques derived from advanced data analytics stand out. IoT enables continuous connectivity between machines, sensors, devices, and systems, allowing real-time data collection directly from the physical environment. This constant monitoring capability generates an enormous amount of information, which is subsequently stored and processed using Big Data technologies. Processing these large volumes of data is essential for AI to extract useful knowledge, identify patterns, and support faster and more accurate decision-making [16-18]. Within this context, Machine Learning—one of the main branches of Artificial Intelligence—plays a crucial role. Through learning algorithms, systems are able to analyze historical data, recognize trends, and continuously learn without direct human intervention. These techniques are widely used in industrial applications such as demand forecasting, predictive maintenance, fault detection, and process optimization. In addition, other complementary techniques, such as Deep Learning, Process Mining, Predictive Analytics, Expert Systems, and Cloud Computing, further expand the potential of AI applications. Deep Learning, for example, enables highly complex analyses and is used in computer vision and pattern recognition. Cloud computing ensures scalability, efficient storage, and processing for AI-based systems. The integration of all these technologies creates an intelligent and autonomous environment capable of improving operations, reducing costs, and increasing efficiency across various sectors, especially in modern industry. This synergy has driven the transition toward more connected, predictable, and data-driven production systems [19-21].

II.3 PRODUCTION PLANNING AND CONTROL

Production Planning and Control (PPC) is a set of essential practices to ensure that the production process takes place in an organized, efficient manner and is aligned with market needs. In industrial environments, PPC seeks to integrate resources, deadlines, productive capacities, and demand, ensuring that production occurs at the right time, in the desired quantity, and at the lowest possible cost. The first phase is planning, which involves demand forecasting, defining production targets, and estimating the required resources. At this stage, sales history, seasonality, inventory levels, and machine capacities are analyzed. Based on this information, the Master Production Schedule (MPS) is developed, a document that guides what to produce, when to produce it, and in what quantity.

The second phase is materials planning, also known as MRP (Material Requirements Planning). It determines which materials will be needed, in what quantities, and when they must be available. The objective is to avoid shortages that interrupt production and excess inventory that generates storage costs. Next comes capacity planning, which assesses whether productive resources—machines, teams, and available time—are sufficient to meet the plan. If constraints are identified, adjustments to the schedule or redistribution of the workload are made. The production scheduling phase defines the sequence of operations on the manufacturing line, optimizing machine usage and minimizing bottlenecks. This stage aims to establish clear and efficient production orders [22-25]. Finally, production control monitors execution in real time, comparing planned results with actual performance. Indicators such as productivity, efficiency, cycle times, and delays are analyzed to support quick decision-making. Thus, Production Planning and Control plays a fundamental role in industrial competitiveness, ensuring more stable, predictable, and economically efficient production processes.

II.4 ELECTRONIC METERS

Electronic Meters are essential devices used to measure, monitor, and record the consumption of electrical energy in residential, commercial, and industrial environments. Unlike traditional electromechanical meters, electronic meters operate using digital components and advanced sensing technologies capable of offering greater precision, real-time monitoring, and improved communication capabilities. Their evolution is strongly linked to the modernization of electrical grids and the global movement toward smarter, more automated energy management systems. One of the key characteristics of electronic meters is their ability to collect high-resolution data. Through embedded microprocessors and electronic sensors, these devices measure voltage, current, power factor, instantaneous consumption, and other electrical parameters with superior accuracy. This precise data collection supports utilities in analyzing consumption patterns, identifying losses, and improving demand forecasting. For consumers, it enables a clearer understanding of their energy usage, encouraging more conscious and efficient consumption habits [26-28]. Modern electronic meters also integrate communication technologies that allow remote data transmission. Through protocols such as RF mesh, PLC (Power Line Communication), or cellular networks, these meters can send consumption information directly to utility companies without the need for manual readings.

This feature forms the basis of Advanced Metering Infrastructure (AMI), which supports bidirectional communication and enables functionalities such as remote connection and disconnection, tariff updates, and automatic reporting of anomalies. In addition to basic measurement functions, electronic meters can include advanced features such as load profiling, event logging, tamper detection, and power quality monitoring. These capabilities increase the reliability of the electrical system by identifying irregularities like voltage dips, spikes, or unauthorized usage attempts. Electronic meters also play a fundamental role in the digital transformation of power distribution networks, often referred to as smart grids. Their integration with data analytics platforms and management systems enables utilities to optimize grid operations, reduce operational costs, and improve energy distribution efficiency [29-31]. Overall, electronic meters represent a significant advancement in metering technology, supporting intelligent energy management, strengthening grid stability, and contributing to the modernization of the electrical sector. As digital technologies continue to evolve, these devices are expected to become even more interconnected, accurate, and capable of supporting future smart energy solutions.

II.5 OPERATIONAL OPTIMIZATION

Operational Optimization is a central concept in modern management, focused on the continuous improvement of production processes, waste reduction, and increased efficiency in industrial and business environments. With the advance of digital transformation, intelligent systems have become indispensable tools for achieving higher levels of operational performance. These systems use Artificial Intelligence (AI), machine learning, real-time data processing, and automation to analyze operations, predict behaviors, and support strategic decision-making. One of the main differentiators of intelligent systems is their ability to collect and process large volumes of data from sensors, machines, corporate systems, and connected platforms. From this set of information, advanced algorithms can identify hidden patterns, diagnose problems, predict failures, and accurately suggest corrective actions. This allows companies to anticipate risks, reduce maintenance costs, and avoid unexpected downtime, directly contributing to increased productivity. In addition, intelligent systems are capable of dynamically optimizing processes. In production lines, for example, they can automatically adjust parameters such as operating speed, task sequencing, resource allocation, and energy consumption, promoting more efficient use of industrial infrastructure.

This real-time adaptability makes the process more agile, reliable, and aligned with current operating conditions [32-34]. Another fundamental aspect of operational optimization is data-driven decision-making. With analytical dashboards, automated reports, and AI-generated forecasts, managers can quickly evaluate operational performance, identify bottlenecks, and define strategic priorities in an informed manner. This reduces uncertainty and significantly improves the quality of decisions. Intelligent systems also contribute to integration between departments, enabling production, logistics, maintenance, and quality to operate in a synchronized way. Communication between machines and corporate systems enables more efficient workflows, full traceability, and greater control over results. In summary, operational optimization supported by intelligent systems transforms the way companies operate, making them more competitive, productive, and prepared for the challenges of the digital era. These systems not only automate tasks but also expand operational intelligence, fostering innovation and sustainability in industrial processes.

II.6 AUTOMATED SYSTEM

An Automated System plays a fundamental role in modern manufacturing environments, especially in the production of electronic devices, where precision, speed, and reliability are essential. As global demand for electronic products continues to rise, industries face the challenge of maintaining high productivity while ensuring strict quality standards. To meet these requirements, automated systems have been widely adopted, transforming traditional production lines into intelligent, efficient, and highly controlled environments. In the manufacturing processes of electronic products—such as circuit boards, sensors, smart modules, and electronic meters—automation enables repetitive activities to be performed with micrometric precision, reducing human error and ensuring consistency.

Stages such as machine soldering, automatic optical inspection (AOI), surface-mount technology (SMT) assembly, and functional testing are now largely carried out by automated systems capable of operating 24 hours a day. In addition to increasing productivity, Automated Systems contribute significantly to improved quality control. Embedded sensors, high-resolution cameras, and inspection algorithms detect defects in real time, allowing immediate corrections and reducing the number of rejected products. This continuous monitoring capability ensures that electronic components meet the safety and performance specifications required by the market. Another important benefit is the integration of these systems with digital platforms and corporate databases. This connection facilitates the collection and analysis of large volumes of operational data, which are used to optimize workflows, predict failures, and schedule preventive maintenance. Data-driven analysis also allows production parameters to be adjusted automatically, ensuring greater energy efficiency and cost reduction. Furthermore, automated systems promote greater flexibility in production lines. Instead of lengthy manual reconfigurations, robots and intelligent machines can be quickly reprogrammed to accommodate new product models or changes in demand, increasing the agility of the production process [35-38]. In summary, the implementation of an Automated System in electronic manufacturing environments represents a significant step toward intelligent production. These systems enhance operational efficiency, improve final product quality, and prepare industries to compete in an increasingly dynamic and technology-driven market.

III. MATERIALS AND METHODS

The proposed computational methodology is based on the principles of Industry 4.0, incorporating advanced digital technologies, real-time connectivity, and intelligent data analysis to enhance Production Planning and Control (PPC) in the manufacturing of Electronic Meters. The objective is to develop an Automated System capable of optimizing industrial operations through Artificial Intelligence (AI) techniques, ensuring greater efficiency, accuracy, and adaptability in production processes. The first stage of the methodology consists of data acquisition and integration, which is typical of Industry 4.0 environments. Sensors, programmable logic controllers (PLCs), Manufacturing Execution Systems (MES), and IoT platforms continuously collect information on machine performance, material consumption, cycle times, inventory, and production orders. These data are transmitted to a cloud infrastructure or an industrial server, where they are stored and organized. In the second stage, data processing is carried out using Big Data tools and preparation pipelines. Data cleaning, standardization, and transformation techniques are applied to ensure quality and consistency. Based on this, AI algorithms—especially Machine Learning—are trained to identify historical patterns, forecast demand for electronic meters, estimate manufacturing times, and detect potential operational bottlenecks. The third stage involves the development of an operational optimization module, responsible for applying mathematical optimization methods—such as Linear Programming, heuristics, and Genetic

Algorithms—to generate efficient production plans. The module considers multiple constraints, including line capacity, material availability, deadlines, scheduled maintenance, and specific requirements of Electronic Meters. The result is an optimized plan that sequences operations, balances workloads, and minimizes idle times. The fourth stage consists of implementing the Automated System, which integrates AI forecasts and optimized plans directly into the production line. This system sends automatic instructions to machines, monitors execution in real time, and continuously compares actual performance with planned targets. In the event of deviations—such as failures, delays, or material shortages—the system triggers a dynamic rescheduling mechanism [39-44]. Finally, the fifth stage involves the visualization and analysis of results, where intelligent dashboards present key performance indicators such as productivity, efficiency, lead time, and reliability. These insights enable continuous adjustments and foster a data-driven improvement culture. Thus, the computational methodology integrates AI, automation, and connectivity, enhancing the level of Operational Optimization in the production of Electronic Meters and aligning the process with Industry 4.0 principles.

III.1 INTENSITY OF THE TECHNOLOGICAL CHALLENGE

The research of this Development project involves uncertainties and challenges, which bring to light the original research premise with the objective of acquiring technical and scientific knowledge to implement tangible solutions. Due to these challenges, the project seeks to:

- Establish and manage the frequency and memory control of traceability devices and their processing capacity related to measurements, in order to maintain a stable state of data transmission and reception (Stages 1 and 2 of Ordinance 2,091);
- Identify patterns related to performance and quality indices to develop KPI control mechanisms and provide optimized decision-making recommendations (Stages 3 and 4 of Ordinance 2,091);
- Perform integrations with the hardware and software stack with minimal data loss and maximum quality in event synchronization to feed Business Intelligence systems (Stages 1 and 2 of Ordinance 2,091);
- Mitigate issues related to scrap, meter nonconformities, and dynamic changes in the production routing based on qualitative charts that generate insights for new solutions (Stages 3 and 4 of Ordinance 2,091).

The project proposes as a solution the development of an intelligent system capable of learning patterns based on events monitored and reported by testing devices, production routing and rescheduling mechanisms focused on electronic meters, and dashboards to support decision-making. The technical aspects of this project consolidate compliance with Ordinance No. 9,835/2022, Annex 1 (Intensity of the Technological Challenge):

I. **Level 4**: Conducting applied research — original research carried out with the objective of acquiring knowledge, primarily directed toward a specific practical objective or target;
II. **Level 3**: Conducting experimental development — systematic work based on pre-existing knowledge acquired through research or practical experience, aimed at producing new products and processes or improving existing ones.

III.2 SOLUTION STRUCTURING

The project includes technical constraints and limitations, making it essential to prioritize testing and validation in order to prove its effectiveness, in accordance with Ordinance No. 9,835/2022, Annex 1 (Solution Structuring).

I. **Solution structuring includes** identifying technical constraints or limitations for the solution and carrying out systematic development with validation tests. The limitations and restrictions are related to technical and security aspects that prevent certain processes, such as:

- **Monitoring area**: The project foresees the development of a traceability and data collection device with RS232 serial communication and via HTTP, TCP, and SSH. However, the monitoring area must be delimited according to the project scope;
- **Development sprints**: The project plans to adopt the technology in a localized space to control production-related events. However, due to time and cost constraints, development sprints were restricted to production control, traceability, quality, and monitoring;
- **Software and firmware upgrades**: The project includes materials and devices to meet its objectives; however, limitations regarding software and firmware upgrades were restricted to current data-processing technologies, which will be documented and delivered to the investing company.

To address these limitations, it is necessary to develop a system that monitors and generates indicators as a preventive premise against the project's technical limitations, highlighting innovation in the context of production rescheduling. For this purpose, several Industry 4.0 pillars will be implemented and incorporated, namely:

- **Data analytics**: To optimize decision-making processes and enable the system to inform and alert about possible harmful causes and effects of nonconforming process events, the project must implement data analysis measures using PyTorch and TensorFlow in Python, within a robust backend hosted on a server that provides adequate hardware for a well-defined Business Intelligence system. Simulation runs must be exhaustive in order to identify and define the best training architecture, thus delivering a viable computational model capable of supporting fluid and objective decision-making;
- **Systems integration**: Due to the business rules of each project module, it is necessary to separate responsibilities (Business Intelligence) through a microservices-based architectural model. For this purpose, stack definitions should focus on testing and simulating scenarios using Kubernetes, Docker, and/or other viable tools to minimize data-processing and systems-integration impacts, consolidating Stage 2 of Ordinance 2,091;
- **Artificial Intelligence**: AI will be used to perform production rescheduling with the premise of capturing causes and effects within the production system, enabling a proactive response to potential problems;
- **Internet of Things (IoT)**: IoT will be incorporated to collect real-time data from connected devices, providing a comprehensive view of the system and enabling dynamic adjustments as needed;
- **Digitalization**: Process digitalization will be a priority to ensure that all project stages are integrated and operate efficiently, enabling more effective management and a rapid response to any challenges that may arise.

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III.4 CURRENT STATUS OF THE SYSTEM

Considering the company's current scenario, there is a Lean Intelligent Manufacturing System (SIME) in place, in which a system foundation has already been developed through a data persistence layer (DBMS) using a MySQL database hosted on a central server. There is also a business layer that uses a set of tools to optimize request processing, such as FastAPI, Celery, WebSockets, among others, all of which use Python as the main programming language, creating a DevOps environment and architecture for communication with the system. Finally, there is a presentation layer that visually displays some production-related raw data, such as the number of meters produced, production targets, and overall line production rates. However, this information is not individualized by each piece of equipment, as it is accounted for through the meter sealing control module.

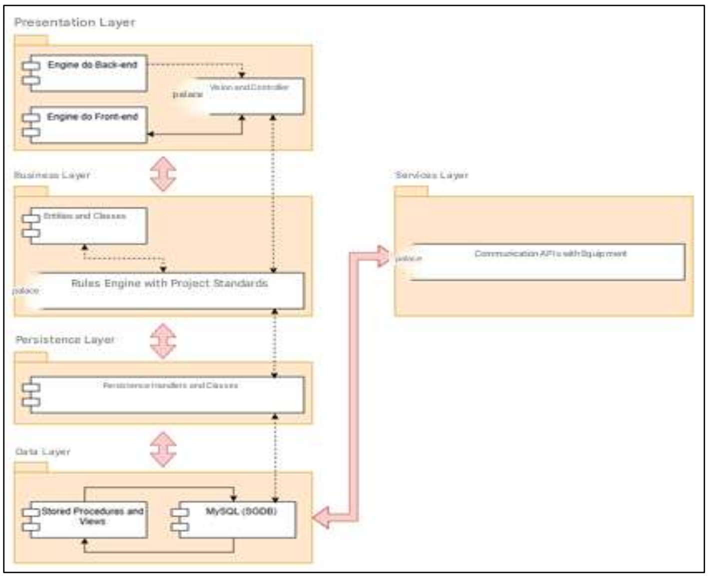

Figure 1: Current Status of the System.
Source: Authors, (2026).

Figure 1 presents a representation of these layers of the existing system, providing a visualization of what they represent and how they are interconnected. This is known as the Model-View-Controller (MVC) model, which revolves around the definition of design patterns that manage stored data, either for display in the presentation layer or for direct data editing through communication with the persistence layer. In summary, this structure was developed within the SIME software and encompasses user and permission management, as well as Business Intelligence through the HORUS API, which organizes data from two main modules: Meter Sealing Control and Inventory Control. These two modules allow monitoring of resource relationships and data on the number of meters produced, with a dedicated dashboard for this purpose. The current project aims to improve the SIME system to encompass the development of an intelligent system for production planning. This system is based on monitoring production events, which indicate actions to be taken to follow the planned schedule, integrating resource management and the Bill of Materials (B.O.M.), currently managed by the JUNDSOFT software, while optimizing business rules with new design patterns.

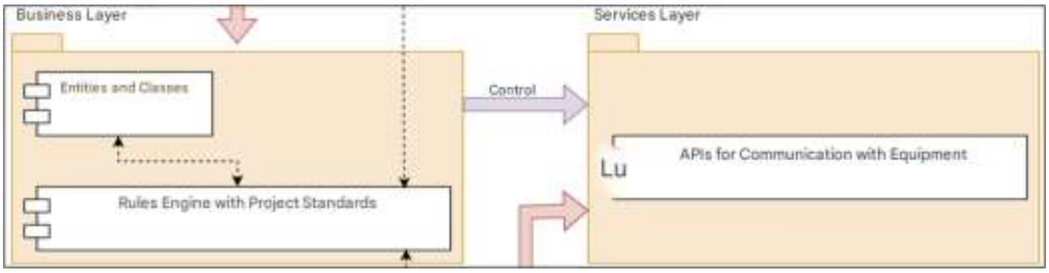

Figure 2: Business and Services Layers.
Source: Authors, (2026).

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III.5 TRACEABILITY DEVICE

In this project, the objective is to integrate the software stacks (services layer API) with the hardware stacks (Traceability Device), which in turn are connected to equipment that generally use RS232 serial communication. The device will serve as the interface to communicate with the equipment and connect them to the internal network, advancing the equipment from a Stage 1 maturity level to Stage 2, where connectivity exists for data collection from each piece of equipment in a pilot line, which will be used to validate the data collection. Some devices in this pilot production line do not have connectivity and will receive a traceability device for data collection, as outlined below:

- **Parameterization Device**: This prototype device will be responsible for configuring the product's memory, recording the serial number, and allowing verification of other quality parameters to ensure that the product meets the customer's purchase order requirements (Verification according to the production order). This system must operate automatically, without operator intervention. Based on the production order number, the system will query via API which configurations and checks need to be performed on the product. Since these configurations are based on customer parameters, the device is called Parameterization.
- **PIMA Asynchronous Serial Output Device**: This device will be a functional test prototype for the product's communication protocol. It will ensure that the product functions and communicates correctly and that the serial code recorded in memory (done by the Parameterization Device) is correct. This stage occurs after the product is permanently closed, ensuring that there is no error in lid exchange or that the mechanical closing process did not damage the product. To determine what should be tested, the system will query via API, based on the production order number, the correct serial number in the production sequence, the communication protocol, and other optional items to be verified.

III.6 SYSTEM MODULES

With the collection of these data, which will be presented in detail in the project scope, it is possible to create new business rules in a new module called the **Production Control Module**, which is responsible for receiving data from each piece of equipment in real time and associating it with production events. These events represent higher-level information that allows for more assertive decision-making. Through this module, the project aims to develop intelligent system software for production planning. The **Traceability Module** is designed to organize data regarding product batches and their journey through the production line. This makes it possible to identify potential batch failures because, in the case of a defect in a meter during the final testing stage, it is possible to track the exact moment the product passed through each piece of equipment. This increases reliability in quality control processes, among other benefits of product traceability. These data allow the creation of business rules for updating the production planning based on traceability information. Meanwhile, the **Quality Control Module** collects, organizes, and makes visible the data related to product quality, allowing for a more comprehensive analysis of detected defects to define standards that will be used to adjust production planning and optimize the company's quality processes. Finally, the **Equipment Module** is not related to the products themselves but to the machines that produce them. Data from this module will be collected to observe patterns in equipment operation, enabling the scheduling of preventive maintenance and providing a basis for predictive maintenance. Additionally, with business rules associated with machine productivity, it is possible to reorganize production planning concerning machine health, operating hours, and reduce failure cycles. Each of these modules is a fundamental component for improving visibility and gathering information to determine production events, which contributed to the creation of an intelligent production planning system. For this, the data to be digitized from each module were defined, and from this data, relevant indicators will be constructed. These are high-level information derived from real-time data and are used to determine production events and shape production planning. The modules and their data and indicators are organized as follows:

- **Production Control:**

  - *Digitized Data:* Equipment utilization rate; production cycle time; number of products manufactured; machine downtime and corrective/preventive maintenance data; raw material consumption.
  - *Relevant Indicators:* Productivity rate; unplanned downtime index; raw material optimization index; reduction rate of losses and rework.

- **Traceability:**

  - *Digitized Data:* Complete batch history (dates, locations, and responsible personnel); detailed production step records; event logs and movements of each product/batch; return and defective product data.
  - *Relevant Indicators:* Real-time visibility index; tracking error reduction rate; response time for fault and return identification; efficiency in locating problematic or defective batches.

- **Quality Control:**

  - *Digitized Data:* Rejection rate per batch; nonconformities identified in inspections; test and quality assessment results; history of rework and repairs performed.
  - *Relevant Indicators:* Defect rate per batch; product compliance with quality standards; number of customer complaints; inspection and quality control time.

- **Equipment:**
    - *Digitized Data:* Equipment operating and downtime; frequency and type of maintenance performed (preventive/corrective); component and part lifespan; energy efficiency and resource consumption data.
    - *Relevant Indicators:* Mean time between failures (MTBF); mean time between corrective maintenance; operational efficiency of equipment; maintenance costs.

IV. RESULTADOS

Equipment, Quality Control, and Production

Initially, a review of the PUR was conducted, along with a study on non-connected devices to define the traceability system. The possibilities for integration with the SIME and JUNDSOFT software were evaluated to obtain metadata from the B.O.M. During this process, the operation of the **Parameterization Device** and the **Asynchronous Serial Output Device (PIMA)** was analyzed. The use of a **Raspberry Pi 5** for data collection and processing was considered, given its memory capacity and compatibility with multiple programming languages, which facilitate real-time solution implementation.

IV.1 PARAMETERIZATION DEVICE

The Parameterization Device was identified as a critical system for the automatic configuration of product memory. Its function is to ensure that each manufactured unit complies with the company's customer specifications, recording the serial number and verifying essential quality parameters. The operation of this device will be fully automated, eliminating the need for manual intervention. Integration via API will allow querying configurations and checks for each produced item, providing more precise and efficient quality control. This approach aims to eliminate human errors and ensure standardization in production, improving product safety and reliability.

IV.2 ASYNCHRONOUS SERIAL OUTPUT DEVICE (PIMA)

The PIMA device is responsible for performing functional tests on the product's communication protocol. This equipment ensures that the serial number recorded in memory is correct and that the product operates as expected. Verification occurs after the product is permanently sealed, preventing issues such as incorrect lid exchanges or mechanical damage during the closing process. The PIMA operation will also be automated, allowing it to automatically query production order information via API. This process ensures the accuracy of the production sequence, validates the communication protocol, and performs additional tests according to customer specifications. Implementing this device aims to increase production reliability and reduce operational failures.

IV.3 INTEGRATION AND DEVELOPMENT OF THE PRODUCTION CONTROL MODULE

From the data collected by these devices, the **Production Control Module** will be developed to consolidate real-time information and transform it into production events. These events enable a deeper analysis of production line performance, facilitating strategic decision-making and optimizing manufacturing management.The integration of these devices with the Production Control Module will enable:

- Real-time monitoring of parameterization and verification processes;
- Automatic alerts for deviations from quality standards;
- Equipment performance analysis and identification of potential production bottlenecks;
- Creation of a traceability history for each manufactured unit.

Integrating the Parameterization and PIMA devices into the new Production Control Module will provide significant benefits for production management, increasing efficiency and reducing operational failures. The use of automated technologies and API integration allows for a more robust approach to quality control and process standardization. During the analyses, it was identified that if mechanical adjustments are needed for device integration into the production environment, **CAD (Computer-Aided Design)** modeling will be used. CAD allows the creation, modification, analysis, and optimization of 3D digital projects, providing precision and efficiency in developing mechanical components.

For this purpose, **SolidWorks** software will be used, one of the most advanced tools for parametric modeling and mechanical simulation. SolidWorks enables detailed part and assembly design, structural analysis, and fit testing before manufacturing. Using this technology will facilitate the creation of supports, enclosures, and other adaptations required to install the devices in the industrial environment, ensuring better performance and integration with the systems.

IV.4 CONNECTIVITY AND NETWORK

A microcomputer kit was considered to process data directly on the devices and communicate with the systems being developed. The **Raspberry Pi 5** is a compact and versatile microcomputer with 8GB of RAM. As shown in the following figure, it is suitable for projects requiring real-time data processing and storage. This model is particularly appropriate to support the development of the Parameterization and PIMA prototypes, as it allows local data processing and the execution of parameterization and production analysis software.

Figure 3: Raspberry Pi 5 8GB.
Source: Authors, (2026).

It has high memory capacity, and its compatibility with multiple programming languages will allow the creation of a robust and agile testing environment, in addition to facilitating integration with sensors and devices. In this context, the **Raspberry Pi 5** will play a highly relevant role in the communication between devices and the software developed for the project. The research conducted during this period highlighted the main contributions, including:

- **Communication Interface:** Can act as a communication gateway, connecting the Parameterization and PIMA devices to the Production Control Module;
- **Data Collection and Processing:** Allows real-time acquisition of data generated by the devices, ensuring integrity and efficient transmission to the analysis systems;
- **Integration via Industrial Protocols:** Supports protocols such as MQTT, Modbus, and OPC UA, enabling interoperability between different equipment and the system;
- **Automation and Control:** Can be used to automate commands, ensuring devices operate according to the guidelines established by the control software;
- **API Connectivity:** Facilitates integration of devices with system APIs, allowing dynamic queries and real-time adjustments to production settings.

The implementation of the Raspberry Pi 5 will enhance system efficiency and reliability, reducing response times and optimizing device management on the production line. This period of activities also included a review of the **Connectivity and Network** point, as described in the PUR assumptions, due to the following condition:

- **Connectivity and Network:** Assumes that the SIME system execution environment, as well as the monitored machines, have the capacity to be connected to SIME through a local network (LAN), either directly or via an intermediate IoT prototype (microcomputers, e.g., Raspberry Pi) and sensors for data collection.

Analyzing this assumption was important to assess the feasibility of communication between the SIPE system and the monitored machines. This initial study helped identify potential technical limitations, such as network infrastructure constraints, and define strategies to ensure effective device connection. Additionally, it enabled the selection of the best approach for data transmission through intermediate devices like the Raspberry Pi, which assist in collecting and sending real-time information. With efficient connectivity, **SIPE** will be able to consolidate operational data reliably, enabling precise analyses to optimize decision-making. Implementing sensors and intermediate devices like the Raspberry Pi will allow the integration of devices connected to the system, ensuring that all equipment can communicate with the production management platform. Furthermore, compatibility with industrial protocols such as MQTT, Modbus, and OPC UA will allow standardized and secure communication between the system's different components. During this project period, research also focused on analyzing frameworks, libraries, and technological protocols essential for system development. Solutions for Front-End and UI/UX development, inter-system communication, database management, and real-time data processing were evaluated. This study identified the most efficient tools to meet project requirements, ensuring technical and operational feasibility, as summarized below.

a) **Front End and UI/UX:**

- **Vue.js:** JavaScript framework for creating dynamic and modular user interfaces;
- **Vue Router:** Library for managing routes in Vue.js applications;
- **Vue I18n:** Plugin for internationalization and localization of applications;
- **VueUse:** Collection of utilities for interacting with APIs and sensors;
- **Quasar/Naive UI:** Component frameworks for developing web, mobile, and desktop applications.

b) **Data Visualization:**

- **ECharts:** Library for creating interactive and dynamic charts;
- **Moment.js:** Library for date manipulation and formatting.

c) **Front End and Back End Communication:**

- **Axios:** HTTP client for asynchronous communication with RESTful APIs.

d) **Back End and Database:**

- **FastAPI:** Framework for building fast and secure APIs, with support for static typing;
- **SQLAlchemy:** ORM library for efficient interaction with SQL databases;
- **Redis:** In-memory database for caching and processing large volumes of data;
- **Celery:** Library for executing asynchronous tasks and distributed processing.

e) **Communication Protocols:**

- **WebSockets:** Protocol for real-time bidirectional communication.

f) **Validation and Testing:**

- **Pydantic:** Library for data validation based on Python typing;
- **Pytest:** Framework for unit, integration, and end-to-end testing.

g) **Internet of Things (IoT):**

- **IoT:** Technology for interconnecting physical devices, enabling real-time data collection and analysis, applied in parameterization and PIMA.

A careful analysis of technologies, tools, and frameworks enabled the selection of solutions suitable for an efficient and structured implementation. The combined use of these technologies will ensure a modular, secure, and high-performance system aligned with the project's objectives. Subsequently, the integrated systems development team focused on researching traceability devices—particularly the Parameterization and Asynchronous Serial Output (PIMA) devices—and structuring the embedded architecture with the Raspberry Pi 5 as the central processing and communication hub. The IoT Developer, Cássia Gabrielly de Souza Lopes, actively participated in the technical review of the PUR, contributing to the validation of hardware components, with emphasis on the Raspberry Pi 5, considered a key element in the collection, processing, and transmission of data from the devices. The researcher conducted detailed analyses of the embedded board's technical specifications, such as its ARM Cortex-A76 processor, 8GB RAM, GPIO interfaces, and support for industrial protocols (MQTT, OPC UA, Modbus), highlighting its potential for integration with the management system and connected devices. She also assessed the feasibility of using serial and USB interfaces for direct communication with production and testing devices. The Raspberry Pi 5 was identified as an essential component for the system architecture, playing a central role in communication between devices and the developed software. The research highlighted its main contributions, including its ability to act as a communication gateway connecting the devices to the Production Control Module, enable real-time data acquisition and processing, integrate via industrial protocols such as MQTT and HTTP, automate operational commands, and provide connectivity with system APIs for dynamic queries and real-time adjustments. Implementing this device will significantly enhance system efficiency and reliability, optimizing device management on the production line. Research was also conducted on the embedded board's electrical diagram, as shown in Figure 4.

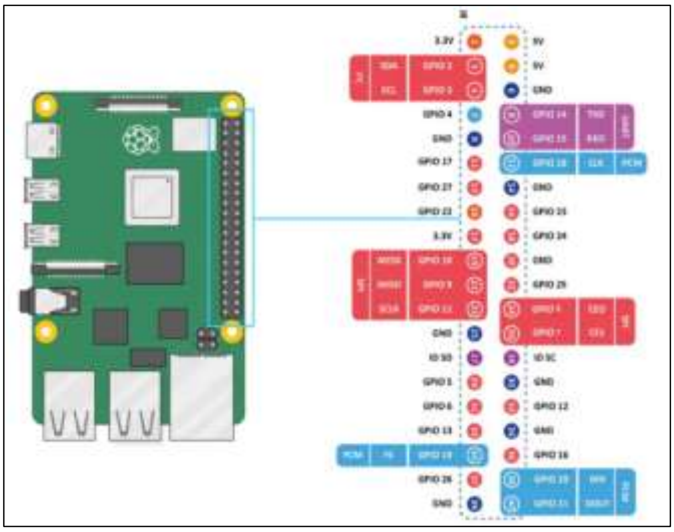

Figure 4: Raspberry Pi5.
Source: Authors, (2026).

This embedded model is the most advanced version of the popular single-board computer line developed by the Raspberry Pi Foundation. With significant improvements in performance and connectivity, the device provides a robust solution for industrial applications, automation, and IoT. Its main technical specifications are as follows:

- **Processor:** Quad-core ARM Cortex-A76, with a frequency of up to 2.4 GHz, delivering performance approximately three times higher than its predecessor, the Raspberry Pi 4.
- **RAM:** Available in 4 GB and 8 GB LPDDR4X-4267 versions, allowing greater energy efficiency and improved performance for multitasking applications.
- **Storage:** MicroSD UHS-I slot, with additional support for storage via PCIe 2.0 (through a dedicated connector), enabling the use of NVMe SSDs for higher read and write speeds.
- **Connectivity:** Includes two USB 3.0 ports and two USB 2.0 ports, plus a Gigabit Ethernet port that supports Power over Ethernet (PoE) when used with an additional module.
- **Graphic Interfaces:** Equipped with two micro-HDMI 2.0 outputs, supporting 4K resolution at 60 Hz and HDR compatibility, ideal for applications requiring high-quality graphics.
- **Graphics Processing:** VideoCore VII GPU with support for OpenGL ES 3.1, Vulkan 1.2, and hardware-accelerated video decoding for H.265 (4Kp60) and H.264 (1080p60).
- **Wireless Connectivity:** Supports Wi-Fi 5 (802.11ac) and Bluetooth 5.0, ensuring stable connections for wireless networks and Bluetooth devices.
- **PCIe Bus:** Integrates a PCIe 2.0 connector, allowing the addition of high-performance peripherals, such as storage controllers or expansion modules.
- **GPIO Pins:** Features 40 GPIO pins compatible with previous Raspberry Pi versions, enabling connections to sensors, actuators, and other devices.
- **Power Supply:** Uses a USB-C connector for power input, supporting 5V/5A, providing sufficient power to operate additional peripherals.

To ensure efficient communication of the traceability and functional testing devices, the Raspberry Pi 5 will be used as an intermediary between the devices and the management system. The Parametrization Device will be connected to the Raspberry Pi via USB or GPIO, allowing automated configuration of the product memory and recording of the serial number. Through API queries, the Raspberry Pi will receive the appropriate configurations and transmit them to the Parametrization Device. The PIMA Asynchronous Serial Output Device will also be integrated with the Raspberry Pi 5, which will serve as a validator of the product’s functionality. The Raspberry Pi will communicate with the PIMA via serial protocol, verifying the correct recording of the serial number and checking the device’s functional communication. In case of inconsistencies, it will be able to log faults and alert the production system in real time. The study identified technical limitations related to network infrastructure and defined strategies to ensure efficient device connectivity.

Compatibility with industrial protocols such as MQTT, Modbus, and OPC UA will ensure standardized and secure communication between system components. During the analyses conducted, no mechanical adjustments were identified as necessary for integrating the devices into the production environment. Therefore, CAD modeling—which allows for the creation and optimization of three-dimensional projects—was not required at this stage. To Marcelo Maia do Nascimento, a senior embedded hardware and software developer, collaborated with the IoT Developer in developing the functional prototype for reading data from electronic meters via the national PIMA protocol. He conducted a comprehensive technical study of PIMA, covering its packet structure (preamble, identifier, size, scope + index, data, and CRC) as well as ANEEL regulatory requirements for interoperability across PLC, RF, and RS-485 networks. He developed the communication logic between the meter and the microcontroller through serial terminals (MTx and MC), with subsequent data transmission to a WebServer embedded in the Raspberry Pi 5, accessible remotely via web browsers.

IV.5 STUDY OF THE PIMA PROTOCOL AND APPLICATION

The Developer conducted an in-depth study of the PIMA protocol, created in Brazil to ensure interoperability among meters from different manufacturers and management systems. The protocol was analyzed in its entirety, from operation over media such as PLC, RF, and RS-485 to its data packet structure, including preamble, identifier, size, scope + index, data, and CRC fields. This deep understanding allowed technical implementations to comply with the 2400 bps speed parameter and the unidirectional asynchronous transmission structure of electronic meters, according to ANEEL specifications.

IV.5.1 Development of the Serial Communication Prototype with WebServer

It will be necessary to adapt the PIMA device, based on the Raspberry Pi 5 microcontroller, to read data sent via the unidirectional serial output of the meters (MTx and MC terminals). Communication between the meter and the microcontroller will be established using physical jumpers, enabling the capture of transmitted packets. The Raspberry Pi 5, with native Wi-Fi connectivity, can be programmed to communicate with a local WebServer, which will display the measurement information in an interface accessible remotely via a browser. The workflow is illustrated in Figure 5.

Figure 5: Serial Communication Prototype with WebServer.
Source: Authors, (2026).

IV.5.2 Data Conversion and Visualization

During the research, it was observed that the structure of the PIMA packet is decoded to extract the data of interest, such as the meter serial number, voltage, current, and power parameters, among others. After reading and decoding, the data will be organized and sent to the WebServer, which will display the values in real time for the operator. This functionality will enable continuous monitoring of energy consumption, promoting greater awareness and control by the consumer. Figure 6 shows the simplified electrical diagram of unidirectional asynchronous serial communication between the meter and the remote device (PIMA Device). On the left side, the serial outputs of the meter are represented, while on the right side, the serial input of the receiving device can be observed. Although the components may vary according to the manufacturer, the basic connection configuration was maintained in this project: the MRx pin of the PIMA device is connected to the MTx pin of the meter, while the MC is grounded. When the meter transmits data through the MTx pin, the device receives the information packets, processes the data, and makes them available on a WebServer developed for visualization. This implementation ensures compatibility with the PIMA standard, allowing proper reading and display of the measurement information.

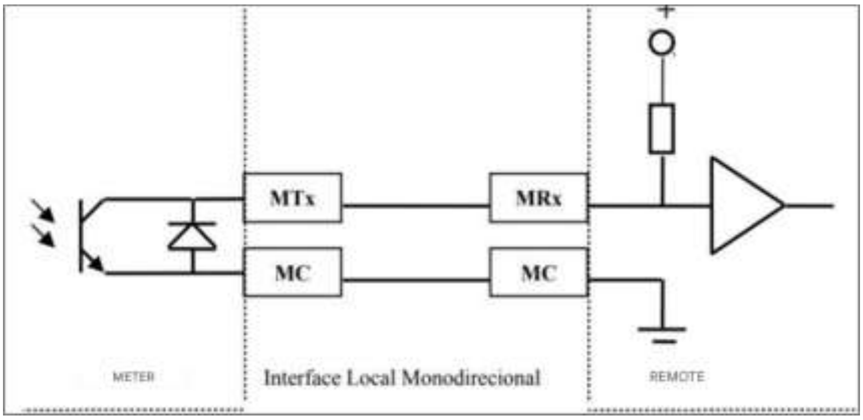

Figure 6: PIMA Electrical Diagram.
Source: Authors, (2026).

The formation of the data packets sent through the asynchronous serial output must follow the specific formatting described below:

- **Preamble:** Initial signaling of a packet. It consists of 2 bytes with the hexadecimal characters AA and 55;
- **Identifier – Meter serial number:** Composed of 5 bytes in BCD format, allowing a 10-digit numbering;
- **Length:** Count of the number of bytes related to the SCOPE + INDEX characters and DATA. Composed of 1 byte;
- **Scope + Index:** Identifier of the type of information to be sent, according to the standard defined in Table 1;
- **Data:** Corresponds to the actual measurement values, presented in BCD format. These data must comply with the definitions of the Application Protocol established by the Brazilian Association of Technical Standards (ABNT);
- **CRC:** Refers to the cyclic redundancy check character of the CRC16 message ($X^{16} + X^{15} + X^2 + 1$), applied over all bytes of the packet, except for the PREAMBLE and the CRC itself.

Automated communication with the meters will enable detailed traceability of the produced units and real-time validation of readings, ensuring greater safety and efficiency on the production line. The development enabled the creation of a continuous flow for reading, decoding, and visualizing meter data, validating the serial number, electrical parameters, and the overall operation of the product. The embedded architecture ensures real-time communication, with the possibility of integration with the SIPE system through APIs, promoting full traceability of the produced units. During the period under analysis, significant hours were dedicated to conducting in-depth technical studies aimed at directly assisting the technical coordinator and the hardware and IoT developers in refining the functional and operational requirements of the system under development.

The author's contribution was essential in consolidating the understanding of demands related to parameterization and communication with electronic energy meters, ensuring that the proposed solutions were aligned with the technical standards of the Brazilian electrical sector, especially with regard to the implementation of connectivity in the PARAMETERIZATION device. In addition, the researcher contributed to defining strategies for integration between physical devices and the embedded and web software architecture, providing a solid foundation for the development and validation of the prototype. The Parameterization Device is an industrial piece of equipment used in the process of configuring and writing parameters to electronic energy meters during the manufacturing phase or final calibration. It plays a fundamental role in customizing meters according to customer technical specifications or current regulatory requirements (e.g., ANEEL, INMETRO, ABNT).

IV.5.3 Objectives and Main Functions

The main objective of the device is to automate the writing and verification of the meter's internal parameters, ensuring its identity, functionality, and compliance with technical standards. Among the functions adopted at Wasion are:

- Writing the serial number to the meter (unique identifier).
- Configuration of tariff tables and calendars.
- Parameterization of demand limits, load profiles, and events.
- Enabling communication modes (e.g., PIMA, DLMS/COSEM).
- Writing technical data such as nominal voltages, base currents, and frequencies.
- Validation and verification of embedded firmware.
- Updating cryptographic keys in meters with advanced security functions.
- Integration with traceability systems and production order databases.

a) Architecture of the PARAMETERIZATION Device

The architecture of the parameterization device includes:

- Central Controller (Arduino Mega microcontroller) with dedicated software.
- Programmable power supply to energize the meter according to its nominal parameters.
- Read and Write Module (via serial port).
- Cryptographic Security Module (in meters with authentication).
- Computer application for configuration and visualization.
- Local database to store parameters and operation logs.

b) Communication Technologies

In discussions with the Technical Team, a study was conducted to identify potential connectivity applications for the device:

- IEC 62056-21 standard optical port: very common in meter parameterization.
- RS-232 or RS-485 serial interface: mainly used for bench parameterization.
- USB port with optical converters: allows connection with parameterization software.
- Wi-Fi / Ethernet interface: in more modern devices with remote control.
- Protocol standards: the most common are PIMA (in Brazil) and DLMS/COSEM (international).

c) Application of the PARAMETERIZATION Device at Wasion

It was identified that Wasion has flexibility in its production lines, which are fully customizable to adapt manufacturing processes as needed. Regardless of the production line, the parameterization device is used at specific stages:

Post-assembly / Pre-closing

- Writing production and identification data.
- Verification of basic operation.

Post-calibration

- Parameterization based on the results of metrological adjustment.

d) Integration with Production Systems

e) Currently, the parameterization device does not have integration with:

- MES (Manufacturing Execution System): enables traceability of the produced unit.
- ERP: for consultation of production orders and customer requirements.
- SQL / NoSQL databases: where parameters are stored and versioned.

Automation/connectivity of the device will minimize human errors, increase productivity, and ensure technical compliance, being a mandatory step in the metrological certification of meters by INMETRO.

a) Standards and Regulations

b) The operation and parameterization of meters follow standards and regulations, among which the following stand out:

- INMETRO Ordinance No. 457/2021: regarding legal metrology of meters.
- ANEEL Resolution No. 844/2019: establishes guidelines for metering and quality.
- ABNT NBR 14522 Standard: specific characteristics of electronic meters.
- IEC 62052 and IEC 62056 Standards: address communication protocols and general requirements.

In the context of the research, the Parameterization Device will be used to:

- Automate the writing of serial numbers and technical parameters of meters.
- Integrate with the traceability module, sending data to an internal WebServer.
- Automatically verify whether the meter complies with the production order specification.
- Record data in an internal database for quality control and statistical analysis.

During this period, the team also assessed the need for mechanical adjustments to the devices, with planned use of SolidWorks software for modeling supports and enclosures. Integration with the SIME and JUNDSOFT systems was considered in defining database structures and communication protocols, establishing a foundation for the development of traceability, production control, and quality control modules. The result of this activity was the consolidation of a robust technical infrastructure for the development of embedded devices, establishing the foundations for functional testing, real-time data collection, and integration with the production management systems of the investing company. During the current month, activities related to the Integrated Systems Development stage advanced significantly, with the direct involvement of the IoT Developer, the Technical Technology Specialist, and the Senior Embedded Hardware and Software Developer. The main focus was on the technical enhancement of the Parameterization Device for electronic meters, a strategic element of the SIPE system to ensure traceability, quality control, and customization of devices according to Wasion’s requirements.

The IoT Developer focused efforts on creating two fundamental diagrams for updating the parameterization device, based on the technical and structural studies carried out in the previous month. From a detailed analysis of the functions, communication ports, and capabilities of the Raspberry Pi 5 microcontroller, the electronic components required to ensure proper communication between physical devices and the production management system were defined. The diagrams were developed prioritizing functional logic compatible with the existing structure of the equipment, respecting component datasheets and carefully distinguishing electrical circuits from electronic circuits. This distinction was essential to ensure that interconnections between signal and power elements were designed safely and accurately. The first diagram, an electrical circuit modeled using Proteus software, focused on integrating the Raspberry Pi 5 into the parameterization device circuit. This simulation was essential to validate interactions among components before physical construction.

In the designed circuit, the Raspberry acts as the main interface, receiving configuration parameters via API and transmitting this information to the meter. Communication between the embedded system and the meter was enabled through a USB-to-TTL adapter, which connects the Raspberry’s serial ports to the pins responsible for reading and writing data on the meter. The device interface was also designed to display the parameterization status to the operator, providing real-time visibility and greater control over the process. Before practical assembly, all connections were meticulously simulated in Proteus, allowing the anticipation of failures such as short circuits, voltage incompatibilities, and risks of damage to sensitive components. This virtual validation ensured the integrity and safety of the circuit. After this phase, physical assembly began in a segmented manner, enabling modular testing at each stage, which increased efficiency in fault identification and contributed to a more stable and secure final integration.

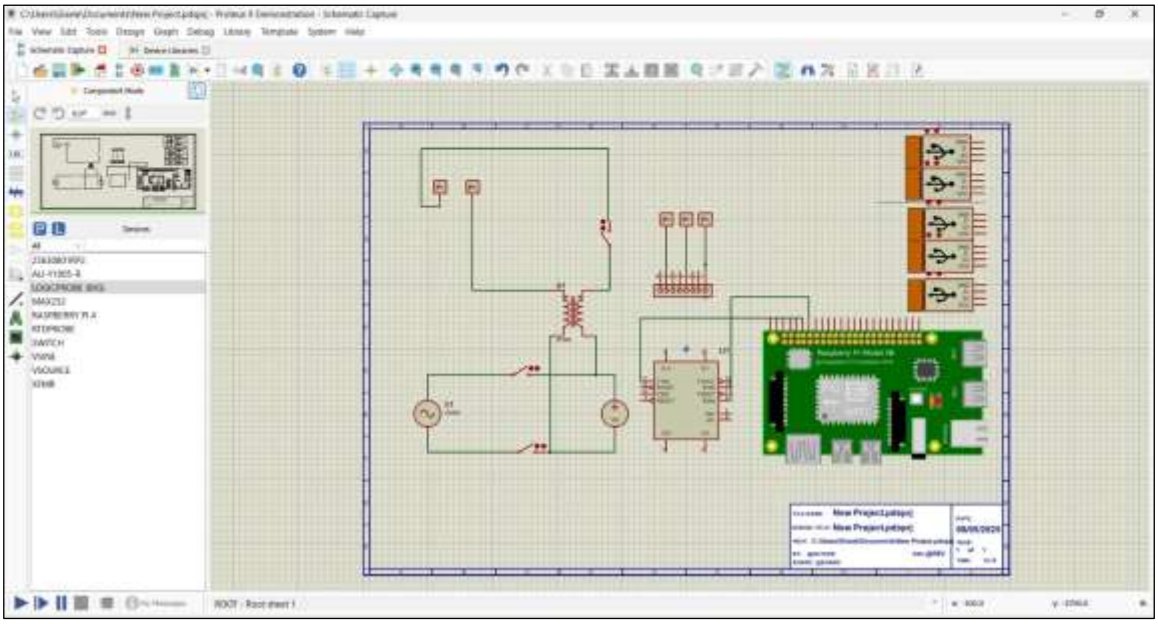

Figure 7: Electrical diagram of the parameterization device.
Source: Authors, (2026).

In parallel, the research deepened its investigation into the company’s production structure, mapping with greater precision the stages of the assembly line in which the parameterization device is inserted. This analysis was formalized through technical flowcharts, as presented in the figure below, and enabled a more detailed understanding of the critical integration points between the equipment and production flows, especially at the pre-closing stage of the meters, known as the Ultrasonic Station. As a result of this mapping, meetings were held with the company’s team to discuss the compatibility of communication protocols with the manufactured meters. In these meetings, emphasis was placed on the technical and regulatory feasibility of implementing the PIMA protocol, considering the requirements of ANEEL, INMETRO, ABNT, and IEC.

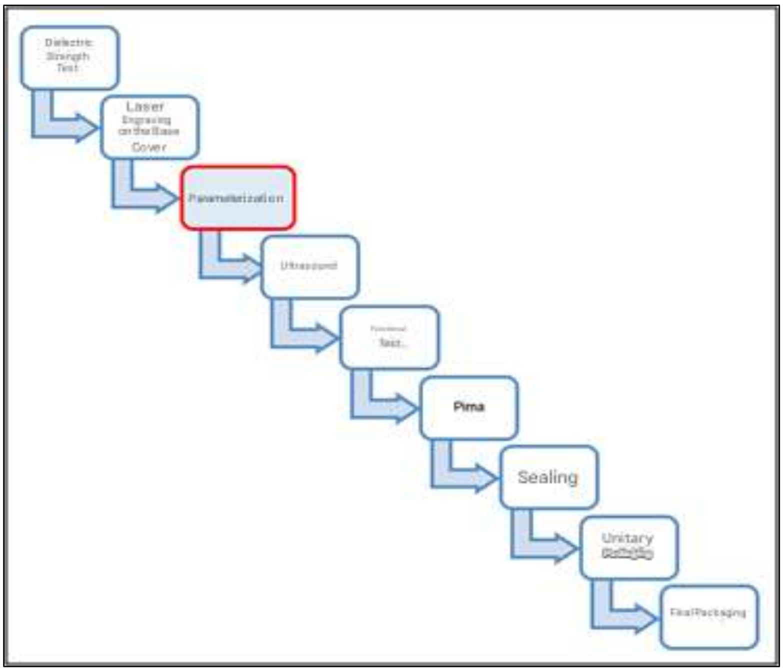

Figure 1 Process Flowchart for Single-Phase Meters.
Source: Authors, (2026).

Simultaneously, the Senior Embedded Hardware and Software Developer directed efforts toward advancing the technical solution of the parameterization device. Initially, the technical and functional requirements of the prototype were defined, with a focus on compatibility with the communication standards adopted by Wasion. Acting as an operational interface, the device was designed to allow operators to configure meters in an automated, secure, and traceable manner. Parameters such as serial number, calibration, firmware version, and operational data were defined as essential to the process. The Raspberry Pi 5 was retained as the core of the system, and logical level converters, USB-to-Serial adapters, and EEPROM modules were incorporated into the project, which are necessary for simulations of writing, reading, and integrity verification. The test circuit was initially modeled using Draw.io. The device firmware was structured using Python, with libraries such as *pyserial* for serial communication and *smbus2* for I²C integration. The initial routines focused on reading unique identifiers, secure write commands, and subsequent validation through reading, ensuring robustness even under conditions of noise or protocol variations, as shown in Figure 9.

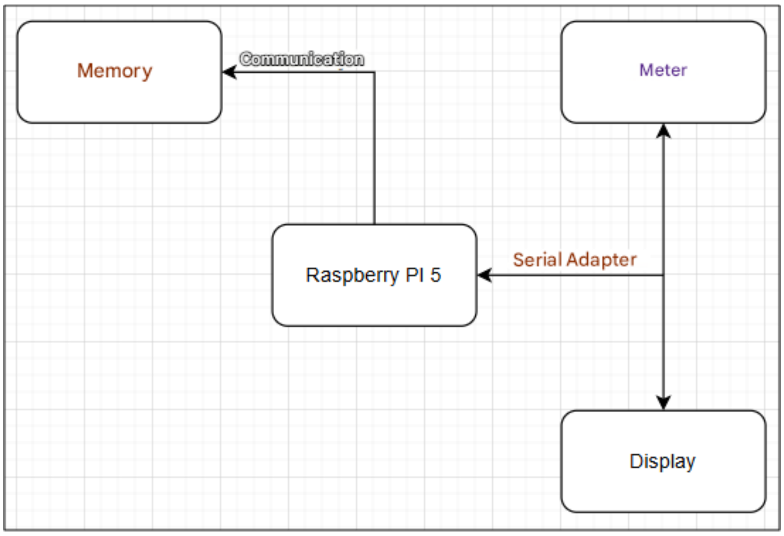

Figure 9: Diagrama para o circuito de teste.
Source: Authors, (2026).

Additionally, an in-depth analysis of the electrical and logical interconnection points was carried out, considering critical aspects such as:

- Power supply compatible with the factory infrastructure (12 V, 24 V, or 220 V AC/DC).
- Shielding against electromagnetic interference, which is common in industrial machine environments.
- Robust and reliable communication interfaces, using standards such as RS-485, Ethernet, MQTT, Modbus, and communication via REST APIs.

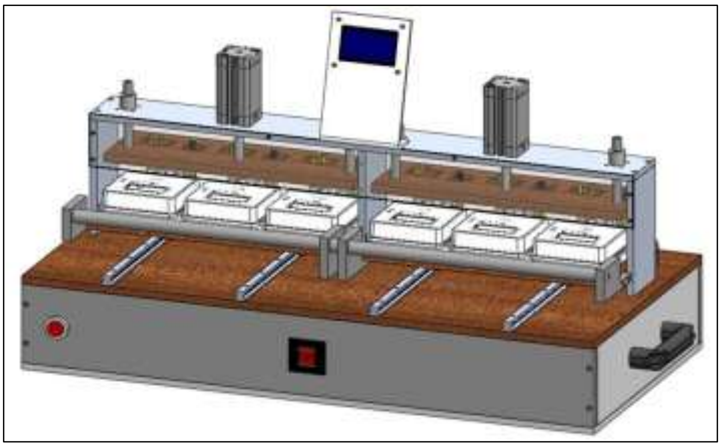

Figure 10: 3D Model of the PIMA Verification Device.
Source: Authors, (2026).

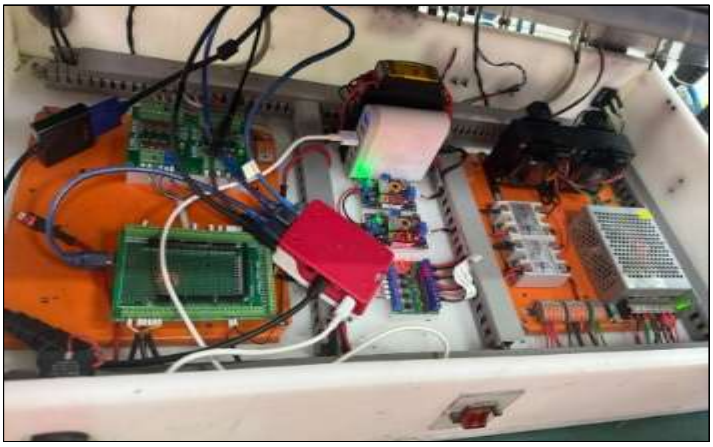

Figure 11: Hardware of the PIMA Verification Device.
Source: Authors, (2026).

Complementing this architecture, the use of Apache Kafka was defined as a distributed messaging platform, serving as the core of data communication between the physical devices (Parameterization and PIMA Device) and the backend systems. Kafka enables real-time event processing, offering (Figure 12):

- High fault tolerance.
- Unlimited horizontal scalability, with the possibility of expanding brokers as data volume grows.
- Long-term data persistence, ensuring reliability in the transport of critical production messages and events.

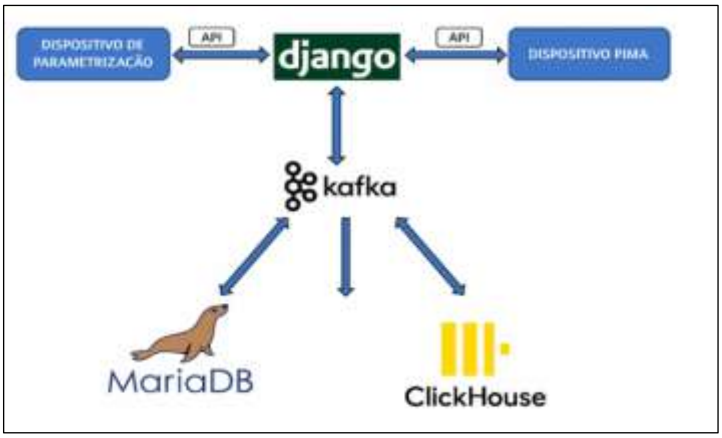

Figure 12: Backend and Communication Architecture Diagram.
Source: Authors, (2026).

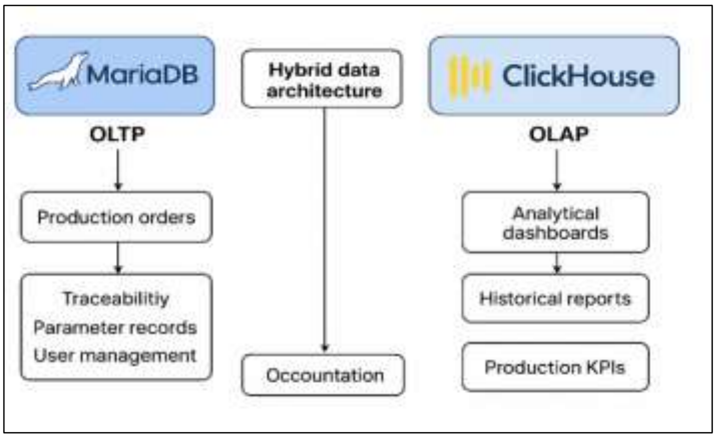

Figure 13: Hybrid architecture for data storage.
Source: Authors, (2026).

Regarding data storage, a hybrid architecture was consolidated, combining two databases with distinct purposes:

- **MariaDB**, adopted for OLTP (Online Transaction Processing), is responsible for managing operational data such as production orders, traceability, parameterization records, and user control. Its selection was based on robustness, relational integrity, scalability, and wide adoption in industrial environments.
- **ClickHouse**, adopted for OLAP (Online Analytical Processing), is intended for managing analytical data, allowing the processing of billions of rows with extremely high-speed queries. Its columnar architecture is ideal for generating analytical dashboards, historical reports, production performance monitoring, and KPIs such as OEE (Overall Equipment Effectiveness) and FPY (First Pass Yield).

MongoDB was also considered during the evaluation process, mainly for storing semi-structured data. However, given the specific project requirements—which demand high transactional consistency and large-scale analytical performance—the technical decision prioritized the combination of MariaDB and ClickHouse, providing robustness and superior performance. Figure 13 clearly and objectively illustrates the hybrid data storage architecture adopted in the project, combining MariaDB (OLTP) and ClickHouse (OLAP), each performing specific and complementary roles within the ecosystem of the developed solution.

IV.5.4 Frontend Development and Operational Interface

The frontend team, composed of Leonardo and Matheus, made significant progress in defining the visual architecture and prototyping system screens, highlighting:

- **Adopted Framework:**
  - Vue.js, combined with Tailwind CSS for styling and Vite for build optimization and agile development.

During subsequent technical meetings (Figures 14, 15, and 16), the use of the Vue.js framework was defined as the basis for system interface development. The choice considered its lightweight nature, ease of integration with WebSocket, modularity, and accessible learning curve, facilitating collaboration among team members. Vue.js will enable the creation of reactive components for real-time data visualization, with reduced complexity in maintenance and scalability of the application.

Figure 14: Vue.js.

Figure 15: Tailwindcss.

Source: Authors, (2026).

Figure 16: Vite.

Source: Authors, (2026).

A Simplified Architecture Diagram was created to clearly, objectively, and visually represent the structure of the system for parameterization and segregation of electronic energy meters. The main goal of this representation was to provide a high-level view of the system's key components, their functional responsibilities, and the communication flows between software modules, embedded hardware, and external backend systems, as shown in Figure 17.

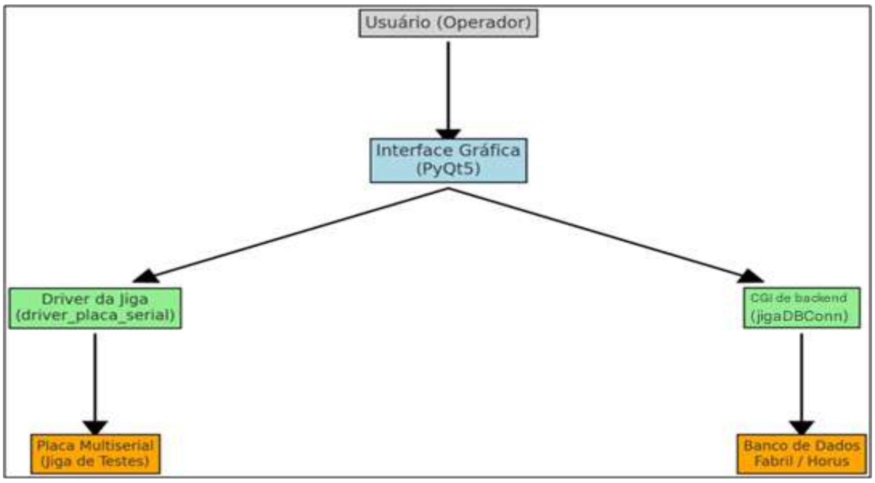

Figure 2 Simplified Architecture Diagram of the Parameterization and Segregation System.

Source: Authors, (2026).

IV.5.5 Main Application – Main

The test results are returned through the carregaMeterStatus slot, which dynamically updates the table with the obtained results, using colors to indicate the success or failure of each meter. At the end of the test batch, if all fields are filled, the interface displays the message “Serial Test Completed!” In the event of critical failures during driver execution, the system calls the erroNoEngine function, which displays an error message to the operator and logs the issue as a critical error. This control reinforces the reliability of the system even under adverse conditions. Another notable feature is the segregar function, which allows the operator to manually record a failed meter outside the automatic flow. When activated, this function opens a segregation window where the operator enters the defective meter's data, and the system records this event in the backend, ensuring full traceability. Additionally, the resetarWidgets function is used at the start of each new work order or in case of a connection error, ensuring the interface is cleared, fields are disabled, and styles are reset for a new work cycle. This structure allows the system to operate in a modular, asynchronous, and visually clear manner. The architecture of paramFechDialog follows industrial software engineering principles, ensuring data consistency, an intuitive operator experience, and seamless integration with other system components. Within this framework, the loginDialog class plays a fundamental role in controlling application access. Its integration with the backend, visual window management, and user feedback mechanisms provide a secure, clear, and efficient interface, aligned with the requirements of industrial environments that handle sensitive data and real-time equipment, as shown in Figures 18 and 19.

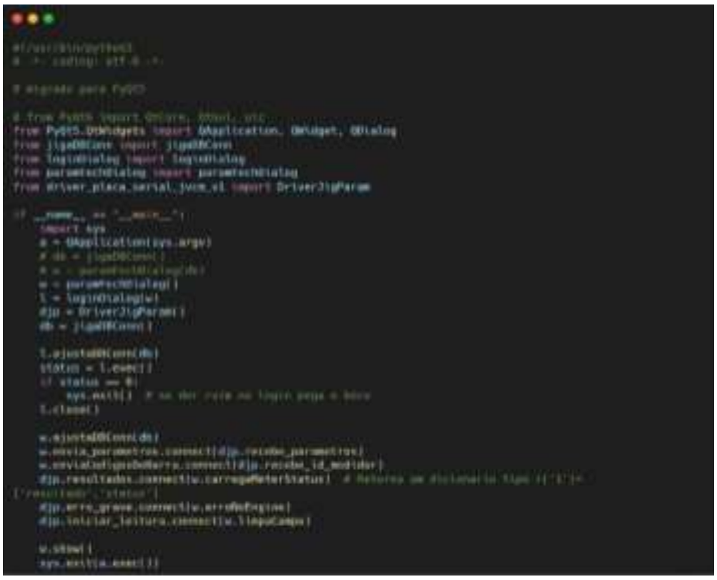

Figure 18: Main.
Source: Authors, (2026).

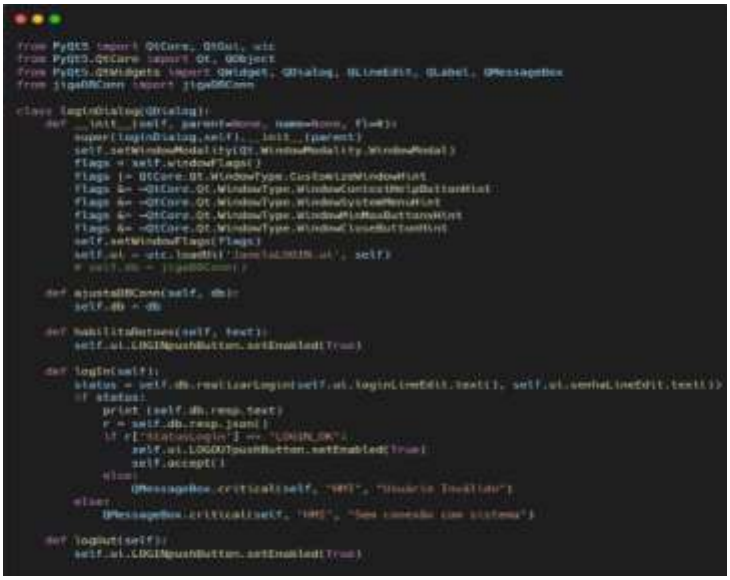

Figure 19: Login.
Source: Authors, (2026).

Therefore, the DialogoSegregarMedidor class represents an important layer of the developed solution. It not only allows operational exceptions to be handled in a user-friendly manner but also reinforces the principles of traceability, data integrity, and compliance with industrial quality and safety best practices. Integrated with the rest of the application through dependency injection and signaling flow, this window helps maintain smooth and secure factory operations even in the face of unexpected events (Figure 20). To ensure consistency and reliability in handling this data, foreign keys (FKs) were applied, and optimized indexes were created based on status, version, and dates, providing better performance for complex queries and greater transactional integrity. Additionally, standardization of possible record states—draft, published, and archived—was established from the beginning, reinforcing the principle of immutability for published versions. This approach, while allowing flexibility during the draft phase, ensured that published versions remained unalterable, guaranteeing the traceability required in a regulated manufacturing environment. To accelerate development and approval cycles, minimal seeds were inserted into the migrations, allowing environments to be initialized with representative data for testing. This strategy reduced the time spent setting up validation scenarios and facilitated the development team's work, enabling them to quickly test functionalities without compromising data integrity. By the end of the first week, the system's relational core was already consolidated, providing a reliable foundation on which subsequent development stages would be built (Figure 21).

Figure 20: Segregate Meter.
Source: Authors, (2026).

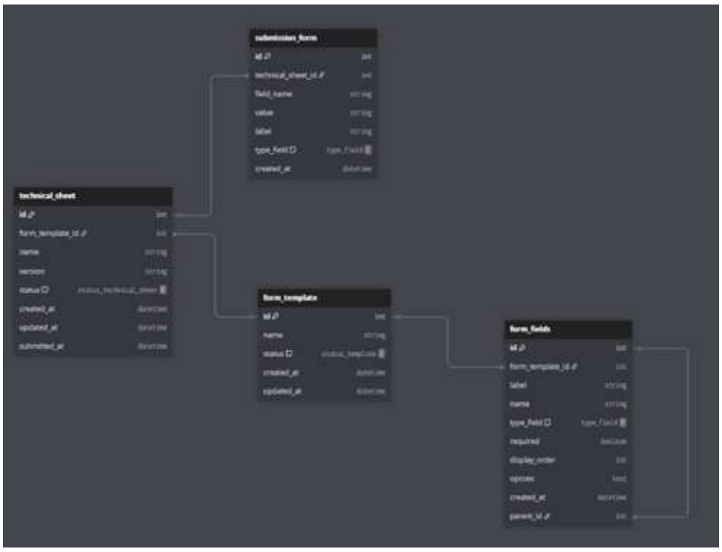

Figure 21: Relational Diagram of the Technical Sheet Module.
Source: Authors, (2026).

IV.6 QUANTITATIVE PERFORMANCE EVALUATION OF THE SYSTEM

Following the gradual implementation of the SIPE modules on the pilot production line for electronic meters, quantitative analyses were conducted to evaluate the system's impact on operational performance. Key performance indicators (KPIs) were monitored before and after the adoption of traceability devices, the Production Control module, and integration with the existing system (SIME). Among the analyzed indicators, the most notable were: productivity rate (meters/hour), average production lead time, rework and rejection rates, average time to identify defective batches, and the unplanned equipment downtime index.

The results indicated a significant reduction in the average lead time of the pilot line, with a decrease in the total time between the start of production and the completion of final testing. An increase in productivity rate was also observed, mainly due to the reduction of unplanned stops and greater predictability in the sequence of operations. In terms of quality, the integration of traceability data and functional testing devices enabled a decrease in rework and rejection rates, as recurring failures were identified more quickly, allowing targeted corrective interventions. Additionally, the time required to locate and isolate problematic batches was significantly reduced, positively impacting the non-conformance analysis process and customer support. Overall, the quantitative results demonstrated that SIPE contributed to increasing the overall efficiency of the pilot line, reducing waste, and enhancing the reliability of production processes, confirming the potential of the proposed approach for industrial environments seeking to adopt Industry 4.0 principles.

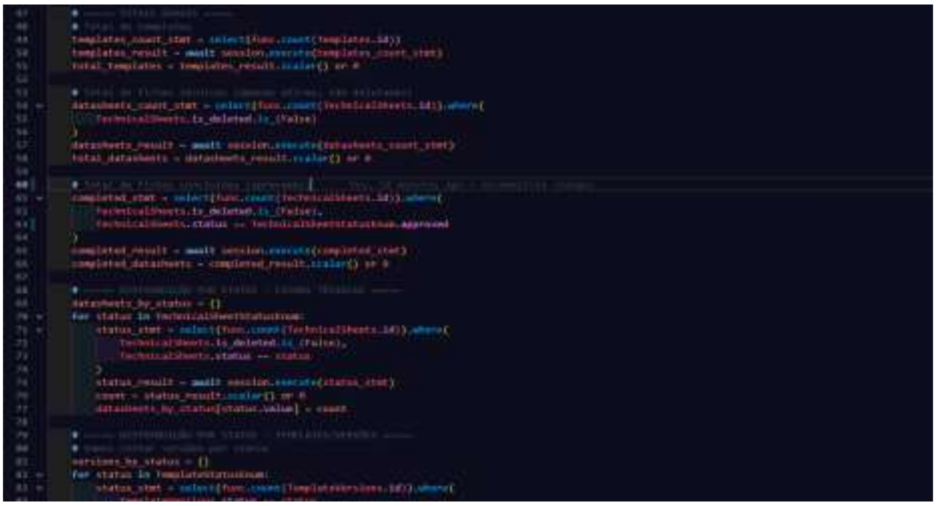

Figure 22: Code for Calculating Statistics and KPIs.
Source: Authors, (2026).

IV.7 IMPLEMENTATION AND EVALUATION OF ARTIFICIAL INTELLIGENCE MODULES

The Artificial Intelligence modules developed within the SIPE framework focused primarily on supporting production planning and replanning, as well as forecasting critical operational variables. Supervised machine learning approaches were used for demand forecasting, cycle time estimation, and identification of production bottleneck patterns. The dataset used to train the models consisted of production order histories, records of meters passing through workstations, machine downtime information, quality test results, and device configuration parameters. These data were extracted from SIME, the new traceability modules, and the Production Control Module, covering a representative period of the pilot line's operation. After data cleaning, normalization, and feature selection, different algorithms were evaluated, including regression, decision trees, and neural network-based models. Model evaluation was performed using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), considering cross-validation scenarios. The results indicated error levels compatible with practical use in decision-support scenarios, allowing cycle times and workload predictions in advance to support production schedule adjustments. In parallel, classification models were investigated to indicate, based on historical patterns, the likelihood of bottlenecks occurring at specific workstations or an increase in the rejection rate. The integration of the AI modules with the Production Control Module allowed forecasts to be consumed in near real-time by the system, generating automatic replanning suggestions in cases of significant deviations. Although the final decision remained the responsibility of the Production Planning and Control (PPC) team, the use of AI-generated recommendations helped reduce response time to unexpected events and made the planning process more proactive and data-driven.

Figure 23: Code for Calculating Performance Score.
Source: Authors, (2026).

IV.8 CASE STUDY ON THE PILOT PRODUCTION LINE OF METERS

To validate the practical applicability of SIPE in a real production environment, a case study was conducted on a pilot production line for electronic meters. The study focused on the integration between the different system modules, demonstrating how the microservices architecture and asynchronous communication between components contribute to operational efficiency and process traceability. The selected pilot line includes workstations with varying levels of automation, from fully connected equipment to devices without native connectivity, which were integrated through the traceability devices developed. SIPE was implemented gradually, starting with the integration of the traceability and production control modules, followed by the implementation of the technical sheet system, and finally the activation of analysis modules and dashboards. One of the most relevant aspects of the case study was the validation of the layered architecture implemented in the system. The presentation layer, developed with Vue and TypeScript, allows operators and managers to view production data in real time through interactive dashboards. The business logic layer, implemented with custom hooks and stores (Zustand), processes and transforms raw data collected from the equipment into actionable information. The communication layer, based on TanStack Query and Axios, manages asynchronous requests to backend services, implementing intelligent caching and automatic retry in case of network failures.

Finally, the backend services layer, composed of the microservices service-auth, service-datasheet, and service-tests, processes business rules and persists data in a distributed manner. The integration between microservices was tested in a real production scenario. When an electronic meter passes through the parametrization device, the system records the event in the traceability module. This event is then processed by the production control module, which updates the production order status and calculates performance indicators. Simultaneously, the technical sheet system is consulted to verify whether the meter specifications comply with the approved template. If any non-conformance is detected, the system generates an alert and records the event in the quality control module, which can trigger automatic production replanning. Service communication was implemented using asynchronous standards with distributed caching (Redis) and exponential backoff retry. For example, when the technical sheet service needs to validate a user profile for approval, it queries the authentication service through the ProfileValidationService. This service implements a cache mechanism with a TTL (Time To Live) of 15 minutes, significantly reducing the number of calls to the external service and improving operation latency. In case of communication failure, the system performs up to 3 attempts with increasing intervals (exponential backoff), ensuring resilience even under unstable network conditions.

During the validation period, a practical scenario demonstrated the effectiveness of the proposed architecture. When a sudden increase in the rejection rate was detected at a functional testing station, SIPE automatically identified the issue through pattern analysis in the traceability data. The production control module correlated the failure events with production batches, identifying that the problem was associated with an improper adjustment on a specific device. The system then issued automatic alerts to the responsible team and suggested partial replanning of production orders, temporarily redirecting the workflow to another set of equipment. This action was executed in less than 15 minutes, from detection to solution implementation, significantly mitigating the impact on daily production targets. The microservices architecture also demonstrated its scalability during the case study. The web service was configured to operate with 4 replicas in the production environment, using Docker Swarm for orchestration and Traefik as a load balancer. This setup allowed the system to maintain high availability even during demand peaks, automatically distributing the load among instances. The technical sheet service, in turn, was dimensioned to process up to 50 signing operations per second, as validated by performance tests, ensuring that the system would not become a bottleneck during critical approval operations. Beyond quantitative benefits, the case study highlighted qualitative gains related to process visibility, standardization of records, and support for decision-making.

Operators and engineers gained an integrated view of the production line, with real-time access to each equipment's data, test results, and production order status. This visibility facilitated root cause identification of recurring problems and allowed prioritization of continuous improvement actions based on objective data. The case study also validated the effectiveness of the electronic signature system integrated with SIPE. During the validation period, over 500 template and technical sheet approvals were processed, all with full traceability through audit logs. The SHA-256 hash system ensured document integrity, and automatic invalidation of signatures when templates were modified ensured that only approved versions were used on the production line. This functionality was particularly relevant to ensure compliance with regulatory requirements and industry quality standards. In summary, the case study on the pilot line demonstrated that the microservices architecture, combined with asynchronous communication, distributed caching, and real-time processing, provides a robust, scalable system capable of supporting the demands of an industrial production environment. The integration of SIPE's different modules enabled more efficient production management, with increased visibility, traceability, and responsiveness to unexpected events, confirming the potential of the proposed approach for digital transformation in manufacturing environments.

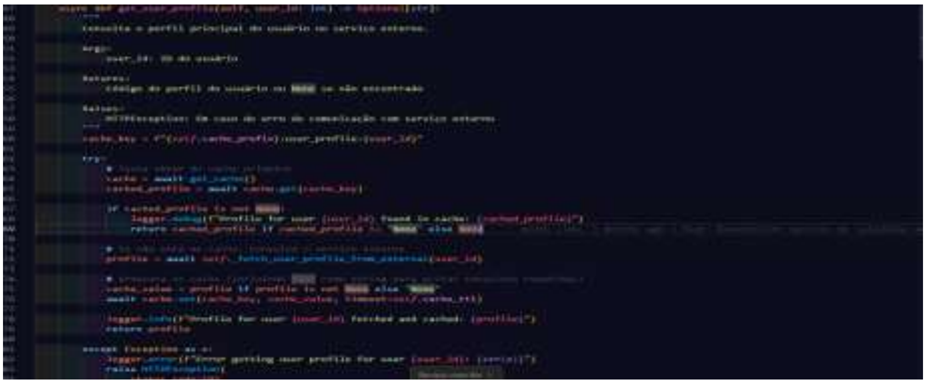

Figure 24: Integration code between microservices with cache and retry.

Source: Authors, (2026).

V. CONCLUSÕES

It is concluded that the development of an Automated System for Control and Production Planning of Electronic Meters with Artificial Intelligence represents a significant advancement in the modernization of industrial processes, aligning technology, efficiency, and reliability. The adoption of the Internet of Things (IoT) enabled the interconnection of production equipment, allowing real-time monitoring, continuous information exchange, and decision-making based on accurate and up-to-date data. The use of traceability and parametrization devices, combined with the asynchronous PIMA serial output, contributed to rigorous control of the production flow, ensuring the individual identification of each electronic meter throughout all stages of the process. This was essential for strengthening traceability, providing a complete history of production, configuration, and testing, as well as supporting quality control through early fault detection and reduced rework.

The integration of electronic meters with the Raspberry Pi 5 (8GB) proved to be an efficient and low-cost solution, offering high performance for data collection, processing, and analysis. The communication interface, together with integration via industrial protocols, ensured interoperability between heterogeneous systems, facilitating automation and control of the production process. Through data collection and processing, combined with artificial intelligence techniques, it was possible to enhance production planning, optimize resources, and increase the reliability of management information. Connectivity with APIs, networks, and digital services expanded system scalability, allowing integration with corporate platforms and cloud environments. Thus, the proposed system proves to be robust, flexible, and aligned with Industry 4.0 concepts, promoting greater operational efficiency, final product quality, and competitiveness in the electronic meter sector.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Jandecy Cabral Leite, Marcelo Maia do Nascimento, Alan Ferreira Pinheiro Tavares, André Barbosa de Lima, Matheus Pereira de Souza, Daniel Gomes Gulart and Marcos Castro de Menezes.
Methodology: Alan Ferreira Pinheiro Tavares, André Barbosa de Lima, Matheus Pereira de Souza.
Investigation: Jandecy Cabral Leite, Marcelo Maia do Nascimento, Alan Ferreira Pinheiro Tavares, André Barbosa de Lima, Matheus Pereira de Souza, Daniel Gomes Gulart and Marcos Castro de Menezes.
Discussion of results: Jandecy Cabral Leite, Marcelo Maia do Nascimento, Alan Ferreira Pinheiro Tavares.
Writing – Jandecy Cabral Leite.
Writing – Review and Editing: Jandecy Cabral Leite and Marcelo Maia do Nascimento.
Resources: Jandecy Cabral Leite and Marcelo Maia do Nascimento.
Supervision: Jandecy Cabral Leite, Marcelo Maia do Nascimento and Alan Ferreira Pinheiro Tavares.
Approval of the final text: Jandecy Cabral Leite, Marcelo Maia do Nascimento.

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VIII. REFERENCES

[1] Saldivar, A. A. F., Li, Y., Chen, W. N., Zhan, Z. H., Zhang, J., & Chen, L. Y. (2015, September). Industry 4.0 with cyber-physical integration: A design and manufacture perspective. In *2015 21st international conference on automation and computing (ICAC)* (pp. 1-6). IEEE.

[2] Zhang, K., Shi, Y., Karnouskos, S., Sauter, T., Fang, H., & Colombo, A. W. (2022). Advancements in industrial cyber-physical systems: An overview and perspectives. *IEEE Transactions on Industrial Informatics*, *19*(1), 716-729.

[3] Leitão, P., Colombo, A. W., & Karnouskos, S. (2016). Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Computers in industry*, *81*, 11-25.

[4] Shadravan, A., & Parsaei, H. R. (2023). The Paradigm Shift From Industry 4.0 Implementation to Industry 5.0. *Application of Emerging Technologies*, *115*, 1.

[5] Nagy, M. (2025). Industria mobilis: Integrating cyber-physical systems, data fusion, and autonomous robotics in Slovak Industry 4.0. *Economics, Management and Sustainability*, *10*(2), 26-46.

[6] Alvarez, M. L., Sarachaga, I., Burgos, A., Estévez, E., & Marcos, M. (2016). A methodological approach to model-driven design and development of automation systems. *IEEE Transactions on Automation Science and Engineering*, *15*(1), 67-79.

[7] Alvarez, M. L., Estévez, E., Sarachaga, I., Burgos, A., & Marcos, M. (2013). A novel approach for supporting the development cycle of automation systems. *The International Journal of Advanced Manufacturing Technology*, *68*(1), 711-725.

[8] Melo, G., Nascimento, N., Alencar, P., & Cowan, D. (2023). Identifying factors that impact levels of automation in autonomous systems. *IEEE Access*, *11*, 56437-56452.

[9] Morrar, R., Arman, H., & Mousa, S. (2017). The fourth industrial revolution (Industry 4.0): A social innovation perspective. *Technology innovation management review*, *7*(11), 12-20.

[10] Philbeck, T., & Davis, N. (2018). The fourth industrial revolution. *Journal of International Affairs*, *72*(1), 17-22.

[11] Castelo-Branco, I., Oliveira, T., Simões-Coelho, P., Portugal, J., & Filipe, I. (2022). Measuring the fourth industrial revolution through the Industry 4.0 lens: The relevance of resources, capabilities and the value chain. *Computers in industry*, *138*, 103639.

[12] Mourtzis, D., Vlachou, E., & Milas, N. J. P. C. (2016). Industrial big data as a result of IoT adoption in manufacturing. *Procedia cirp*, *55*, 290-295.

[13] Ur Rehman, M. H., Yaqoob, I., Salah, K., Imran, M., Jayaraman, P. P., & Perera, C. (2019). The role of big data analytics in industrial Internet of Things. *Future Generation Computer Systems*, *99*, 247-259.

[14] Khan, M., Wu, X., Xu, X., & Dou, W. (2017, May). Big data challenges and opportunities in the hype of Industry 4.0. In *2017 IEEE International Conference on Communications (ICC)* (pp. 1-6). IEEE.

[15] Malek, Y. N., Kharbouch, A., El Khoukhi, H., Bakhouya, M., De Florio, V., El Ouadghiri, D., ... & Blondia, C. (2017). On the use of IoT and big data technologies for real-time monitoring and data processing. *Procedia computer science*, *113*, 429-434.

[16] Chen, Y. (2020). IoT, cloud, big data and AI in interdisciplinary domains. *Simulation Modelling Practice and Theory*, *102*, 102070.

[17] Lampropoulos, G. (2023). Artificial intelligence, big data, and machine learning in industry 4.0. In *Encyclopedia of data science and machine learning* (pp. 2101-2109). IGI Global.

[18] Kibria, M. G., Nguyen, K., Villardi, G. P., Zhao, O., Ishizu, K., & Kojima, F. (2018). Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. *IEEE access*, *6*, 32328-32338.

[19] Venkatesh, D. A. N. (2019). Reimagining the future of healthcare industry through internet of medical things (IoMT), artificial intelligence (AI), machine learning (ML), big data, mobile apps and advanced sensors. Artificial Intelligence (AI), Machine Learning (ML), Big Data, Mobile Apps and Advanced Sensors (October 28, 2019).

[20] Manoharan, K. G., Nehru, J. A., & Balasubramanian, S. (2021). Artificial intelligence and IoT. *Springer*, *10*, 978-981.

[21] Rane, N. (2023). Integrating leading-edge artificial intelligence (AI), internet of things (IOT), and big data technologies for smart and sustainable architecture, engineering and construction (AEC) industry: Challenges and future directions. *Engineering and Construction (AEC) Industry: Challenges and Future Directions (September 24, 2023)*.

[22] Lăzăroiu, G., Andronie, M., Iatagan, M., Geamănu, M., Ștefănescu, R., & Dijmărescu, I. (2022). Deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in the internet of manufacturing things. *ISPRS International Journal of Geo-Information*, *11*(5), 277.

[23] Usuga Cadavid, J. P., Lamouri, S., Grabot, B., Pellerin, R., & Fortin, A. (2020). Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing*, *31*(6), 1531-1558.

[24] Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability*, *12*(2), 492.

[25] Shi, H., Cao, G., Ma, G., Duan, J., Bai, J., & Meng, X. (2022). New progress in artificial intelligence algorithm research based on big data processing of IOT systems on intelligent production lines. *Computational intelligence and neuroscience*, *2022*(1), 3283165.

[26] Zhao, X., Wang, R., Wang, Y., & Wang, L. (2020, September). Design and realization of metering production plan management system. In *Journal of Physics: Conference Series* (Vol. 1633, No. 1, p. 012155). IOP Publishing.

[27] Vesikkala, T. (2017). Lean Optimization for Electric Meter Production.

[28] O'driscoll, E., & O'donnell, G. E. (2013). Industrial power and energy metering–a state-of-the-art review. *Journal of cleaner production*, *41*, 53-64.

[29] Duncan, B. K., & Bailey, B. G. (2004). Protection, metering, monitoring, and control of medium-voltage power systems. *IEEE Transactions on Industry Applications*, *40*(1), 33-40.

[30] Benyoucef, D., Bier, T., & Klein, P. (2010, June). Planning of energy production and management of energy resources with Smart Meters. In *2010 International Conference on Advances in Energy Engineering* (pp. 170-173). IEEE.

[31] Li, D., Qu, J., Su, Q., Du, B., Guo, L., Zhang, Q., & Cai, W. (2018, July). Research on Smart Electric Energy Meters Manufacturing Technology Program Based on RFID. In *2018 Eighth International Conference on Instrumentation & Measurement, Computer, Communication and Control (IMCCC)* (pp. 1538-1541). IEEE.

[32] Oteri, O. J., Onukwulu, E. C., Igwe, A. N., Ewim, C. M., Ibeh, A. I., & Sobowale, A. (2023). Cost optimization in logistics product management: strategies for operational efficiency and profitability. *International Journal of Business and Management. Forthcoming*.

[33] Gamal, H., Albahri, S., Essa, H., Srivastava, M., Alghamdi, N., & Shaikh, W. (2024, February). Driving operational excellence: Cost savings and performance optimization through tripping and connection time optimization. In *International Petroleum Technology Conference* (p. D021S077R002). IPTC.

[34] Kaydos, W. (2020). *Operational performance measurement: increasing total productivity*. CRC press.

[35] Liao, H. C., Lim, Z. Y., Hu, Y. X., & Tseng, H. W. (2018, July). Guidelines of automated optical inspection (AOI) system development. In *2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP)* (pp. 362-366). IEEE.

[36] Abd Al Rahman, M., & Mousavi, A. (2020). A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry. *Ieee Access*, *8*, 183192-183271.

[37] Ronchi, M., Regattieri, A., Gamberi, M., & Cafarella, C. (2025). Multi-criteria selection of image acquisition technologies for automatic optical inspection in assembly lines. *The International Journal of Advanced Manufacturing Technology*, 1-20.

[38] Goti, A. (2025). Automated Optical Inspection (AOI) Based on IPC Standards.

[39] Oluyisola, O. E., Bhalla, S., Sgarbossa, F., & Strandhagen, J. O. (2022). Designing and developing smart production planning and control systems in the industry 4.0 era: a methodology and case study. *Journal of Intelligent Manufacturing*, *33*(1), 311-332.

[40] Alaji, F. (2024). *Enhancing Energy Efficiency in Production Lines Through Advanced Process Monitoring and Control System* (Doctoral dissertation, Magyar Agrár- és Élettudományi Egyetem).

[41] Bueno, A., Filho, M. G., Carvalho, J. V., & Callefi, M. (2021). Smart production planning and control model. In *Perspectives and Trends in Education and Technology: Selected Papers from ICITED 2021* (pp. 253-267). Singapore: Springer Singapore.

[42] Hoffmann, M. (2019). *Smart agents for the Industry 4.0* (pp. 226-297). Springer: Berlin, Germany.

[43] Lai, C. A. (2022). System level of intelligent manufacturing. In *Intelligent Manufacturing* (pp. 53-105). Singapore: Springer Nature Singapore.

[44] Sundar, P. S., Chowdhury, C., & Kamarthi, S. (2024). Industrial Internet of Things Enabled Kata Methodology of Assembly Line Productivity Improvement: Insights from a Case Study. *Processes*, *12*(11), 2611.