Development of a System for Demonstration of Maintenance 4.0 Technologies in an Advanced Manufacturing Didatic Plant

Matheus Calheira Guimarães de Oliveira[1*], Arthur Gabriel Lima Paim[1], Bruno Santos Junqueira[1], Nilton Figueiredo e Silva Neto[1], Robson Carlos Souza Rosario Junior[1], Erick Giovani Sperandio Nascimento[1,2]

[1]SENAI CIMATEC University; Salvador, Bahia, Brazil; [2]Surrey Institute for People-Centred AI, University of Surrey; Guildford, Surrey, United Kingdom

Industry 4.0 has introduced new maintenance management paradigms, demanding innovative training and implementation solutions. This article proposes a system architecture integrating sensors, IoT devices, data analysis, and condition-based maintenance techniques to serve as a demonstration and learning platform. The proposed methodology involved four steps, culminating in the system's prototyping. The system enables the visualization of how Maintenance 4.0 technologies impact performance, cost, and compliance indicators. The study concludes that the developed system effectively demonstrates these technologies, supporting the training of professionals in a controlled environment where the benefits of applying Maintenance 4.0 solutions can be observed.
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In the era of Industry 4.0, the latest technological advancements are increasingly integrated into industrial systems [1]. According to Shaheen and Németh, maintenance management within industrial manufacturing is significantly shaped by technologies such as the Internet of Things (IoT), cloud computing, big data, artificial intelligence (AI), and cyber-physical systems. In this context, Miguel and colleagues (2022) emphasize that Maintenance 4.0 applies Industry 4.0 tools and resources to enhance the industrial maintenance process. On one hand, it leverages interconnectivity through connected sensors, programmable logic controllers (PLCs), and machines as data sources; on the other hand, it utilizes data processing capabilities to detect trends and support maintenance decision-making [2].

Cachada and colleagues (2018) argue that most current industrial maintenance strategies remain largely reactive or preventive, with predictive approaches limited to critical systems. This is despite the increasing volume of data generated on the shop floor and the availability of emerging information and communication technologies (ICTs), such as IoT, big data, advanced analytics, cloud computing, and augmented reality [3]. However, the maintenance paradigm is shifting. Maintenance is now recognized as a strategic activity and a key contributor to productivity in industrial systems.

Condition-based maintenance (CBM) has emerged as a crucial management strategy within this evolving landscape. CBM focuses on forecasting equipment degradation, operating under the principle that most failures follow a progressive path from normal operation to malfunction rather than occurring instantaneously [4].

Maintenance 4.0 utilizes advanced sensors and data analytics to monitor equipment health and predict failures, enabling proactive and well-planned interventions. To ensure that professionals and students fully understand and apply these concepts and technologies, providing systems that demonstrate the shift from traditional reactive and preventive strategies to data-driven, predictive approaches is essential. This paper presents a system developed and implemented at the SENAI CIMATEC Advanced Manufacturing Plant (AMP), featuring a communication and operational architecture designed to align with Industry 4.0 tools and methods.

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Address for correspondence: Matheus Calheira Guimarães de Oliveira. Avenida Orlando Gomes, 1845. Zipcode: 41650-010. Salvador, Bahia, Brazil. E-mail: matheus.guimaraes@fbter.org.br.

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Figure 1 presents the method for developing the system.

Literature Review

The literature review identified three key studies illustrating systems development for demonstrating or experimenting with maintenance technologies aligned with Industry 4.0.

The first study [2] proposes a testbed designed to translate the Maintenance 4.0 paradigm into an educational context using the Project-Based Learning (PBL) approach. This testbed focuses on the maintenance of machines and robots, collecting data from a network of interconnected equipment to support condition monitoring and maintenance decision-making via machine learning. To ensure Industry 4.0 connectivity, the system employs industrial communication protocols (e.g., ProfiNet, ProfiBus, EtherCat) and conventional networking technologies (e.g., Ethernet, WiFi 802.11, Bluetooth). A supervisory control and data acquisition (SCADA) system is utilized for data visualization.

The second study [5] describes a testbed developed to demonstrate maintenance technologies using a FESTO didactic production system. It incorporates an Industrial Internet of Things (IIoT) platform that generates work orders, dispatches maintenance resources via an autonomous robot, and delivers step-by-step instructions for executing maintenance tasks. Built on a cyber-physical production system, the testbed features advanced communication protocols, including OPC-UA, Modbus, WebSockets, IIoT gateways, and application programming interfaces (APIs). Data visualization and analysis are managed through a cloud-based Computerized Maintenance Management System (CMMS) supported by AI-driven analytics.

The third study [6] presents an educational platform developed for remote training in Maintenance 4.0. It leverages the Open System Architecture for Condition-Based Maintenance (OSA-CBM) framework, developed by MIMOSA, to structure data flow. This modular platform comprises three main components: (1) Maintenance 4.0 and CBM; (2) Failure diagnostics and prognostics; and (3) Data-driven maintenance management. The system is designed for integration with external platforms such as CMMS and ERP via Layer 2 or 3 network connectivity (e.g., database or server layer). Additionally, a remote interface was developed to configure data acquisition systems.

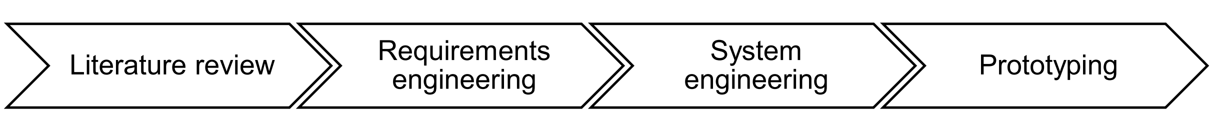
Requirements Engineering

System requirements define what a system should accomplish and how it operates [7]. According to Valente (2020), requirements are generally functional or non-functional. Functional requirements specify the system's expected services and functionalities, while non-functional requirements outline operational constraints and quality of service attributes.

Requirements were identified based on the literature to guide the development of the proposed system. These requirements informed both the functional capabilities and operational characteristics of the system. Mirka and colleagues (2020) emphasize that laboratory environments should adhere to industrial standards in architecture, database schema, and component design.

Accordingly, the system considers the requirements outlined in Institute of Asset Management [8], particularly those related to asset management training, awareness, and competence. At SENAI CIMATEC's Advanced Manufacturing Plant (AMP), maintenance procedures and

Figure 1. The method used for the system development.



competencies were structured according to standard processes.

The primary functional requirements identified include:

- Continuous monitoring of equipment through real-time data collection, a fundamental aspect of CBM;
- Insight generation based on the collected data;
- Support for planning and scheduling maintenance tasks using condition-monitoring techniques.

Maintenance actions may be triggered by either online data (enabled by machine learning) or on-site measurements using portable devices.

The non-functional requirements include:

- Data security, achieved through the use of encrypted communication protocols;
- System scalability, allowing support for a growing number of users and devices;
- Adaptability and flexibility, ensuring compatibility with various test configurations, usage scenarios, and IoT devices;
- Responsiveness, with near-instantaneous updates, even under high data loads.

System Engineering

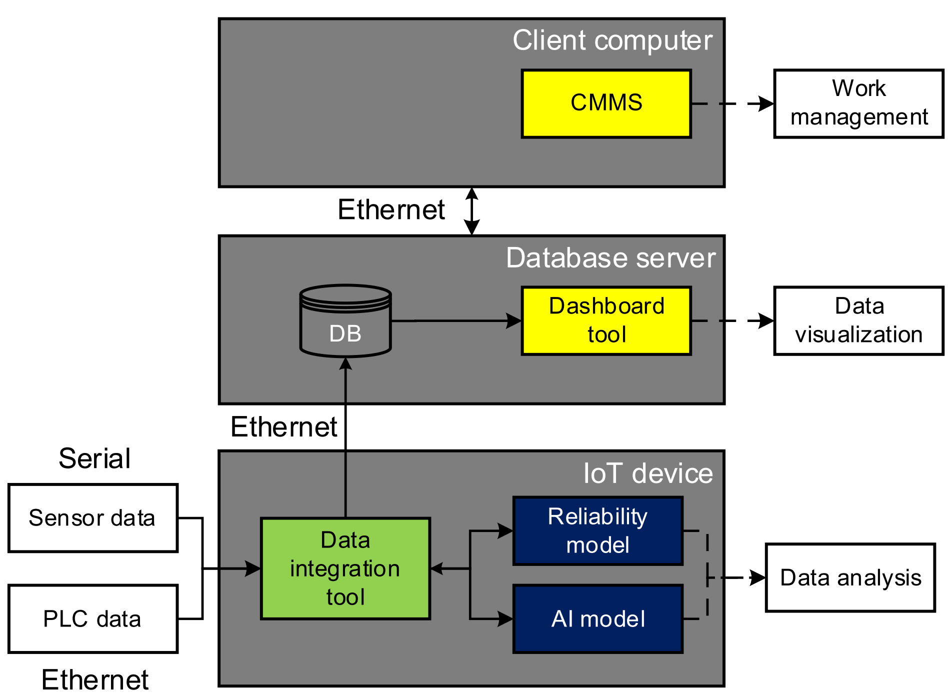
Wasson (2015) notes that the definition of systems engineering varies across disciplines. In this work, systems engineering refers to the interdisciplinary approach encompassing requirement interpretation, architectural design, and prototype development.

The two main focuses of this study—justifying the use of systems engineering—are the integration of Industry 4.0 ICTs (i.e., information technologies [IT] and operational technologies [OT]) and the delivery of maintenance operations such as planning, scheduling, and execution [9].

The system's communication architecture, illustrated in Figure 2, includes sensors, programmable logic controllers (PLCs), an IoT device, a database server, and a client computer. To determine the critical parameters for monitoring an induction motor's performance, a Failure Mode and Effects Analysis (FMEA) was conducted. This analysis played a key role in identifying the variables essential for assessing the motor's operational condition.

The Maintenance 4.0 operational system architecture, depicted in Figure 3, comprises two types

Figure 2. Communication architecture of the system.



of monitoring: online and offline. Online monitoring utilizes mathematical models and AI algorithms to remotely visualize alarms, alerts, anomaly detection, failure diagnostics, and prognostics. Offline monitoring involves periodic on-site analysis scheduled through the CMMS for predictive maintenance. This is achieved by identifying faults using the frequency spectrum of the induction motor and its temperature. The latter activity is facilitated by portable instruments and sensitive inspections following established procedures.

Prototyping

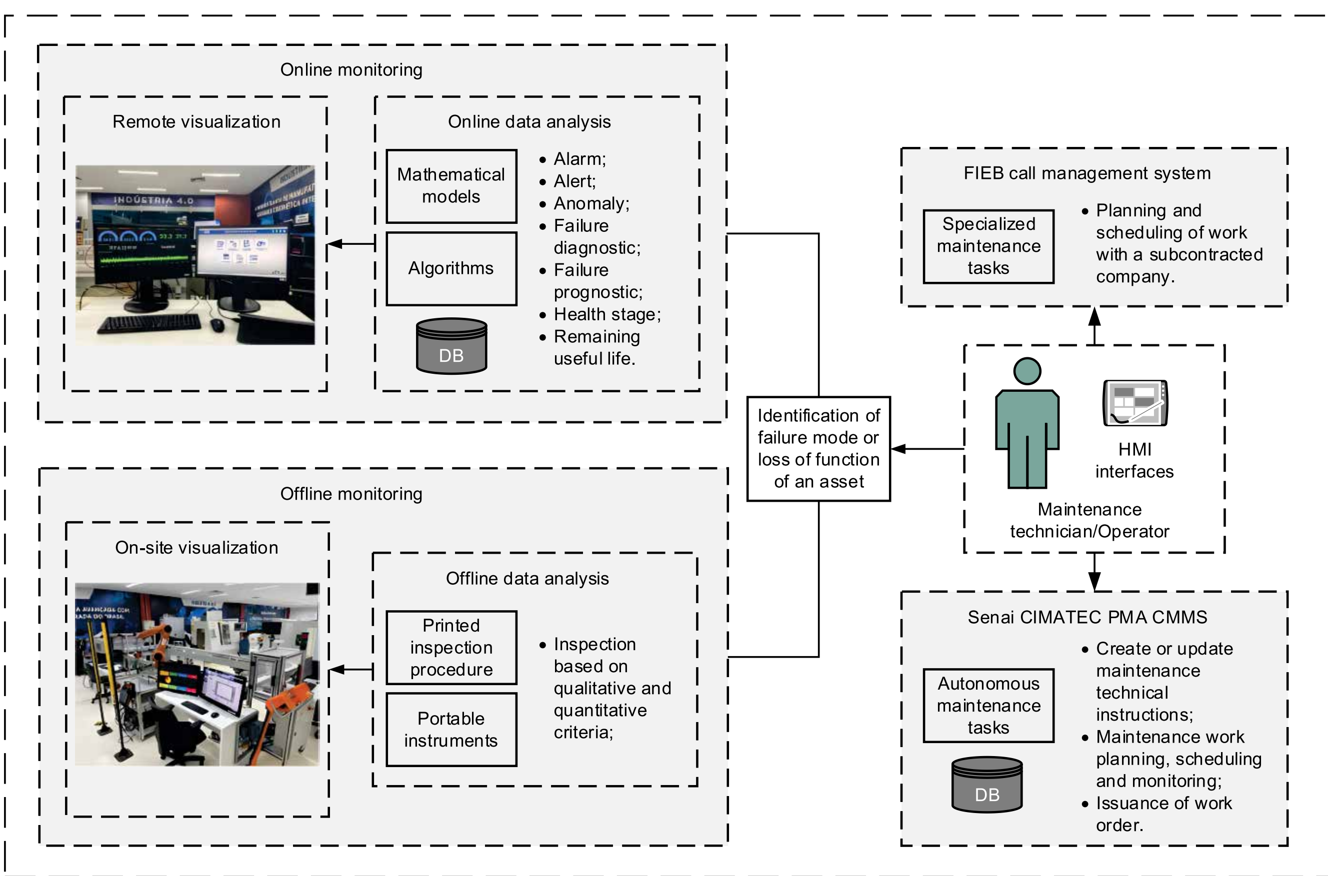
This phase involved implementing the system's communication architecture and developing the scripts required to initiate the monitoring and maintenance of an induction motor. The system was designed to monitor the conveyor belt induction motor located at the SENAI CIMATEC Advanced Manufacturing Plant (AMP) transport station. This motor—specifically a VEMAT 0.5 hp single-phase asynchronous motor, model 7HB 71B—is critical to operations, as its failure results in a complete halt of the AMP system.

Sensor selection considered factors such as maximum vibration levels and the need for physical contact with the motor. The ADXL345 accelerometer was selected for vibration monitoring based on its sampling rate compatibility with the motor's low rotational speed and expected signal frequency. To measure the motor's surface temperature, a GY-906 infrared temperature sensor was used.

Ambient conditions—specifically temperature and humidity—were collected using a DHT22 sensor. Due to budget constraints, voltage and current sensors were not acquired, although their inclusion was recommended during the FMEA analysis.

The selected sensors transmitted data to a Raspberry Pi 4 Model B (RASPi) IoT device using

Figure 3. Maintenance 4.0 operational system architecture.



I2C and SPI communication interfaces, chosen based on the available input pins. However, the I2C interface presented limitations related to cable length when connecting the vibration and temperature sensors. To address this, two P82B715P I2C bus extenders were installed. Additionally, operational data from the Rockwell CompactLogix L18ERM PLC—such as the motor's on/off status and frequency from the inverter—was transmitted to the RASPi via Modbus TCP.

Data analysis models and algorithms were developed once all devices were configured and tested. The RASPi utilized Node-RED to integrate data from sensors and PLCs and feed it into the analysis models. Two analytical models were implemented: a reliability model and an artificial intelligence (AI) model. The reliability model, based on a proportional hazard model [11], used operational time and temperature data to estimate the motor's Remaining Useful Life (RUL). In the absence of historical failure data, expert elicitation generated synthetic data for estimating covariate parameters.

The AI model used a Multilayer Perceptron (MLP) algorithm to classify the motor's condition into four categories: healthy, light deterioration, moderate deterioration, and severe deterioration. Inputs included motor speed, vibration, and temperature. The model employed Adaptive Moment Estimation (Adam) [12] as its optimizer and was trained using real healthy-state data and synthetically generated degradation data. Vibration data was created using a modified sinusoidal function, while temperature data followed a modified sigmoid pattern, both implemented in Python.

Processed data—including sensor readings, PLC values, and model outputs—were transmitted via Ethernet to a Microsoft SQL Server Express database. Grafana was employed for data visualization due to its compatibility with SQL databases and capacity for creating clear and interactive dashboards. This setup gave operators real-time insights to support proactive maintenance and minimize unplanned downtime. Finally, a client computer connected to a Computerized Maintenance Management System (CMMS)—developed by SENAI CIMATEC—was used to manage maintenance activities and integrate real-time monitoring information.

Results and Discussion

Implementing the Maintenance 4.0 system at the AMP represents a significant advancement from traditional reactive and preventive approaches toward a predictive and proactive maintenance strategy. By integrating advanced data analytics, reliability engineering, and AI-driven diagnostics, the system demonstrated the potential to optimize maintenance planning, improve asset availability, and reduce operational costs.

Integration with SENAI CIMATEC's CMMS enabled dynamic planning and scheduling of maintenance activities based on actual equipment conditions rather than relying solely on fixed intervals. This real-time alignment of maintenance tasks with machine health supports greater efficiency and reliability.

The system architecture emphasized scalability, flexibility, and data security. Although Modbus TCP was implemented without encryption for prototyping purposes, the use of IoT gateways to convert insecure protocols into secure communication is strongly recommended for real-world industrial applications.

Despite the unavailability of real-world failure data, the AI and reliability models enhanced visibility into motor health, providing insights previously dependent on expert intuition. The capability to visualize and analyze real-time data also contributed to user education by demonstrating practical applications of predictive maintenance techniques.

Conclusion

This paper presented the development of a system designed to demonstrate Maintenance 4.0 technologies within a didactic Advanced Manufacturing Plant (AMP). Integrating information and communication technologies for real-time data collection and analysis and automated maintenance management creates a robust educational tool for professionals and students alike.

The results indicate that the system significantly enhances the teaching and application of modern maintenance strategies aligned with Industry 4.0 principles. It fosters technical and strategic skill development, preparing users to meet the demands of contemporary industrial environments.

Further assessment of the system's educational effectiveness should be conducted using it in actual classroom and training settings. At SENAI CIMATEC, the system is expected to be adopted in undergraduate, technical, and continuing education programs across industries of various scales. Future work may include evaluating student satisfaction and learning outcomes to refine system architecture, procedures, and educational materials.

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