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INTEGRATING IIOT SENSORS TO REDUCE UNPLANNED DOWNTIME AND MAXIMIZE EFFICIENCY

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Rezumat. *Lucrarea analizează integrarea senzorilor IIoT în procesele de fabricație din ingineria industrială, cu scopul de a transforma liniile de producție tradiționale în sisteme inteligente și interconectate. Se propune implementarea unei rețele de senzori capabile să colecteze date în timp real despre parametri cheie, cum ar fi temperatura, vibrațiile și consumul de energie. Datele colectate sunt transmise prin protocoale de comunicație industrială către o arhitectură Edge-to-Cloud, unde sunt procesate și vizualizate folosind tablouri de bord intuitive. Pe lângă implementarea în lumea reală, studiul include și o simulare a funcționării sistemului IIoT, utilizată pentru a valida arhitectura propusă și pentru a analiza comportamentul procesului de fabricație în diverse scenarii operaționale. Simularea permite evaluarea impactului monitorizării active asupra performanței sistemului înainte de implementarea industrială la scară largă. Studiul evidențiază tranziția de la monitorizarea pasivă la cea activă, permițând mentenanța predictivă și reducând timpii de nefuncționare. De asemenea, examinează beneficiile legate de optimizarea resurselor și interoperabilitatea cu sistemele existente. Rezultatele demonstrează o eficiență operațională îmbunătățită și susțin adoptarea principiilor Industriei 4.0.*

Abstract. *This paper analyzes the integration of IIoT sensors into manufacturing processes from industrial engineering, aiming to transform traditional production lines into intelligent and interconnected systems. It proposes the implementation of a sensor network capable of collecting real-time data on key parameters such as temperature, vibrations, and energy consumption. The collected data is transmitted through industrial communication protocols to an Edge-to-Cloud architecture, where it is processed and visualized using intuitive dashboards. In addition to real-world implementation, the study also includes a simulation of the IIoT system operation, used to validate the proposed architecture and to analyze the behavior of the manufacturing process under various operational scenarios. The simulation enables the assessment of the impact of active monitoring on system performance prior to full-scale industrial deployment. The study highlights the transition from passive to active monitoring, enabling predictive maintenance and reducing downtime. It also examines benefits related to resource optimization and interoperability with existing systems. The results demonstrate improved operational efficiency and support the adoption of Industry 4.0 principles.*

Keywords: IIoT, Sensors, Downtime, Efficiency, Maintenance

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1. Introduction

On the threshold of the Industry 4.0, the manufacturing sector faces unprecedented pressure to increase competitiveness and reduce operational costs. Industry 4.0 does not merely represent a technological upgrade, but a fundamental paradigm shift that places data at the center of the decision-making process [1]. The concept of "Zero Downtime" has become the central pillar of modern manufacturing strategies, aiming for the complete elimination of unplanned downtime, which has historically represented the primary source of inefficiency and financial loss in factories [2].

The significance of choosing this topic derives from the economic reality of 2026, where informational latency and intuition-based decisions are no longer sustainable. In a conventional production line, failures are often detected only at the moment of their occurrence, generating a domino effect that compromises delivery deadlines and the quality of final products. Through the integration of IIoT sensors, machinery gains a voice, continuously transmitting vital parameters such as vibration, temperature, and energy consumption, thereby enabling the implementation of predictive maintenance (PdM) [3].

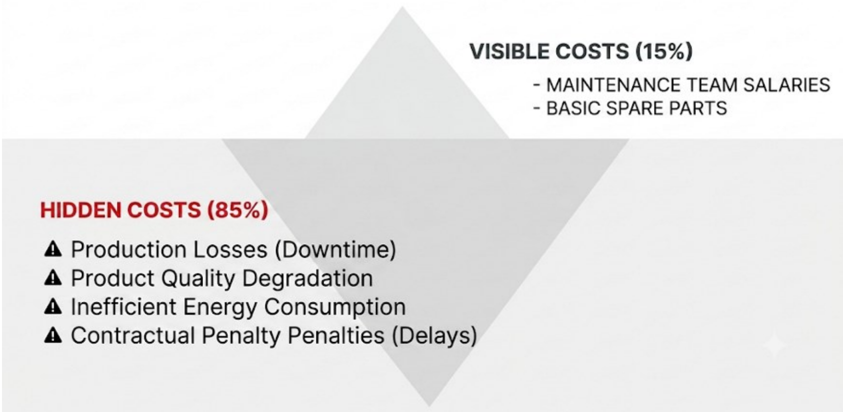

Fig. 1. A comparative analysis of explicit versus implicit costs

Fig. 1 illustrates the iceberg metaphor applied to the costs generated by operational inefficiency and unplanned downtime in the industrial environment. It can be observed that the visible costs, representing only approximately 15% of the total, are limited to direct expenses such as maintenaFnce team salaries and spare parts. However, the most significant portion of the economic impact, estimated at 85%, is represented by hidden costs, which include production losses, quality degradation, energy waste, and contractual penalties [10]. This visualization underscores the necessity of implementing IIoT-based predictive maintenance solutions, which are capable of identifying and mitigating these losses that often remain unquantified in traditional monitoring systems.

The primary objective of this project is to demonstrate the viability of an Edge-to-Cloud architecture in transforming a conventional machine tool into a smart asset. The aim is not only to collect data but also to process it locally to reduce network traffic, followed by an advanced cloud-based analysis to generate overall equipment effectiveness (OEE) indicators and early warnings. The research methodology combines the theoretical analysis of integrated manufacturing systems with a practical approach based on a case study applied to a computer numerical control (CNC) machine tool, evaluating the economic impact through Return on Investment (ROI) models.

2. Fundamental Concepts on Computer Integrated Manufacturing (CIM) and IoT

2.1. The Evolution of Manufacturing Systems: From Automation to Digitalization

Manufacturing systems have come a long way from craft workshops to today's fully automated factories. The Third Industrial Revolution introduced the concept of Computer Integrated Manufacturing (CIM), which aimed to integrate all production activities under computer control. However, CIM often remained limited by rigid hierarchical structures and the existence of 'islands of automation', systems that, while high-performing on their own, could not communicate efficiently with each other due to proprietary protocols.

The transition toward Industry 4.0 and the IIoT represents the breaking down of these barriers. While CIM focused on local control and sequential automation, Industry 4.0 introduces the concept of Cyber-Physical Systems (CPS) [5], [14], where physical entities are digitally mapped and interact in real time. Digitalization does not merely mean replacing paper with screens, but creating a continuous data flow that feeds artificial intelligence algorithms capable of optimizing processes without constant human intervention [6], [15].

Table 1 presents a comparative analysis between the traditional CIM (Computer Integrated Manufacturing) model and the new IIoT paradigm, highlighting the fundamental transition toward Industry 4.0. It can be observed that, unlike the hierarchical and rigid structure of the CIM model, the IIoT approach proposes a decentralized ecosystem based on horizontal and vertical communication via open protocols such as OPC UA and MQTT [4], [12]. This evolution enables the shift from preventive maintenance, based on fixed time intervals, to predictive maintenance grounded in the real-time monitoring of operating parameters and artificial intelligence algorithms [6], [11]. Thus, the table underscores that the adoption of IIoT technologies does not merely represent a technological shift, but a strategic optimization of data flow to ensure the interoperability and scalability of modern manufacturing systems.

Table 1. Comparison between CIM and the IIoT-based approach in the context of digitalization

	CIM (Industry 3.0)	*IIoT (Industry 4.0)*
Structure	Hierarchical	Decentralized / Interconnected ecosystem
Communication	Proprietary, isolated protocols	Open standards (OPC UA, MQTT)
Data	Periodically collected, reactively used	Real-time flow, predictively used
Decision-making	Centralized, fixed-logic based	Distributed, Machine Learning-based
Maintenance	Preventive	Predictive

The next step involves utilizing AI analysis through an Edge-to-Cloud architecture, which is essential for implementing predictive maintenance algorithms. This technological sequence culminates in achieving Industry 4.0 standards, where the 'Zero Downtime' objective is supported by a system capable of autonomously optimizing processes and eliminating unplanned downtime.

2.2. Industrial Internet of Things (IIoT) Architecture in an Industrial Context

The IIoT represents the application of IoT technologies within industrial environments, where reliability, precision, and security requirements are significantly more stringent than in commercial applications. A robust IIoT architecture is structured into four fundamental layers, ensuring a fluid information flow from the sensor to the strategic decision [7].

The data acquisition layer (Field Layer) comprises smart sensors and devices that interact directly with the physical environment. These sensors not only measure physical quantities but can also perform basic pre-processing. The Edge Layer acts as a local intelligence hub, where industrial gateways collect data from multiple sources, filter noise, and perform protocol conversion [8]. This stage is essential, as it reduces the network bandwidth required for transmitting data to the cloud and enables instantaneous responses at the machine level.

The Cloud/Platform Layer acts as the analytics engine, where data is stored in time-series databases and processed utilizing Big Data algorithms to identify patterns and anomalies [9]. Ultimately, the Application Layer provides the user interface through intuitive dashboards, integrations with Computerized Maintenance Management Systems (CMMS), and management reporting tools. This modular architecture enables system scalability, facilitating the addition of new machinery or sensors without disrupting the existing structure [4].

2.3. The Role of Real-Time Monitoring in Operational Efficiency (OEE)

Overall Equipment Effectiveness (OEE) is the fundamental metric used to measure the productivity of an industrial process. It is composed of three key factors: Availability, Performance, and Quality. In traditional systems, OEE is calculated manually and post-factum, which limits the capacity to correct deviations in a timely manner.

Real-time monitoring through IIoT transforms OEE from a historical statistic into an active management tool. By automatically detecting micro-stops and speed degradation, operators can intervene immediately. Predictive maintenance plays a vital role here, preventing drops in availability by anticipating failures. The analysis of the collected data enables the identification of the 'Six Big Losses' in manufacturing: equipment failures, setup and adjustments, idling and minor stoppages, reduced speed, process defects, and reduced yield at startup.

The standard formula for calculating OEE is expressed by the following equation:

$$\mathbf{OEE} = \frac{\text{Actual operating time}}{\text{Planned operating time}} \times \frac{\text{Actual production}}{\text{Maximum production}} \times \frac{\text{Good units}}{\text{Total units}}$$

Through sensor integration, each term of this equation is continuously monitored, providing a level of precision that eliminates human reporting errors and establishes a solid foundation for optimizing material flow and energy consumption.

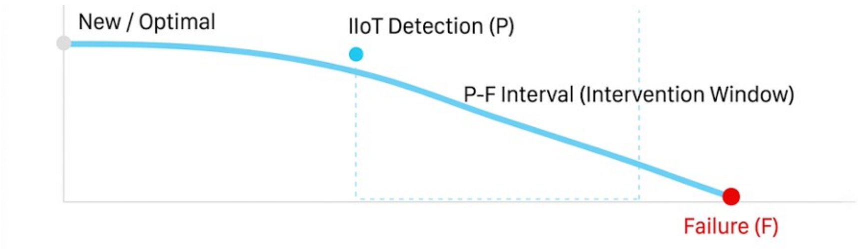

Fig 3. Curba P-F (Potential Failure – Functional Failure)

The degradation process of industrial equipment and the significance of the intervention timing are graphically represented by the P-F interval curve, detailed in the Fig. 3. This illustrates the transition from an optimal operating state to the point of functional failure (F), highlighting the role of early detection through IIoT technologies (P). The P-F interval, defined as the intervention window, represents the time available for maintenance teams to act before a total breakdown occurs. The utilization of smart sensors allows for the identification of anomalies much earlier than traditional methods, maximizing this interval and facilitating the shift from reactive to predictive maintenance. This approach is essential for reducing downtime and optimizing asset lifecycle.

3. Sensing and Data Acquisition Technologies

3.1. Classification of Sensors Used in Industrial Environments

Sensors represent the sensory system of the smart factory, capable of detecting subtle changes in equipment condition long before they become visible or audible to a human operator. Selecting the appropriate sensor depends on the specifics of the monitored mechanism and the identified failure modes.

Table 2. Matrix of Sensing Technologies in Smart Manufacturing

Sensor Type	*Technology / Principle*	*Specific Application*	*Direct Benefit*
Vibration	Piezoelectric / MEMS	CNC Spindles, Pumps, Fans	Bearing wear detection
Temperature	RTD / IR	Bearings, Motor housings, IT Racks	Fire / Seizure prevention
Energy Consumption	Current Transformer	Motor power supply lines	Load anomaly detection
Pressure	Piezoresistive	Hydraulic systems, Air lines	Leak and blockage detection
Proximity	Inductive / Capacitive	Assembly lines, Robots	Operation cycle monitoring
Acoustic	Ultrasonic	Gearboxes, Pneumatic systems	Early crack detection

Vibration sensors (accelerometers) are essential for monitoring rotating components. Vibration spectral analysis enables the identification of imbalances, misalignment issues, or defects in bearing raceways. Temperature sensors (thermocouples, PT100, or infrared sensors) are utilized to monitor the thermal stress of motors and electronic circuits, serving as precise indicators of lubrication problems or overloads.

The matrix presented in Table 2 synthesizes the primary sensing technologies utilized within the context of Smart Manufacturing, highlighting the versatility and direct benefits of integrating IIoT sensors into industrial monitoring. The correlation between the selected sensor type and specific failure modes can be observed.

3.2. Communication Protocols for Smart Manufacturing

The efficiency of an IIoT system is determined by the capacity of its components to exchange information in a secure and standardized manner. Communication protocols act as a common language between sensors, PLCs, and software platforms.

OPC UA (Open Platform Communications Unified Architecture) has become the de facto standard for interoperability in Industry 4.0. Unlike its predecessors, OPC UA is platform-independent and offers an object-oriented data model, meaning that data is delivered along with its context (for instance, not merely the value '25.4', but also the fact that it represents a temperature in degrees Celsius from the main motor). Security is a native element in OPC UA, utilizing encryption and digital certificates to ensure data integrity from the machine level up to the ERP system.

MQTT (Message Queuing Telemetry Transport) is preferred for data transmission to the Cloud due to its extremely lightweight nature (low overhead). Based on a publish-subscribe model, it allows Edge devices to send data to a central broker, from where it is distributed to multiple applications (Dashboard, Database, Alert System). MQTT is ideal for unstable or low-bandwidth connections, making it an extremely robust protocol in challenging industrial environments [12].

3.3. Integrating Sensors with Programmable Logic Controllers (PLCs) and SCADA Systems

The modernization of a production line does not always imply replacing legacy equipment (brownfield integration). IIoT gateways can be utilized to extract data from existing PLCs using traditional protocols such as Modbus TCP or Profinet, subsequently converting them into modern data streams.

SCADA systems remain the central pillar for local operational control, yet IIoT integration extends their capabilities. Data from supplementary vibration or energy sensors, which are not critical to the PLC's control logic, can be routed in parallel with control data. This hybrid approach enables machine health monitoring without overloading the limited CPU resources of the PLC. By mapping PLC tags directly to energy analytics portals, companies can track the real-time energy cost per unit of product, facilitating process optimization for sustainability and economic efficiency.

4. Architecture of the Proposed Monitoring System

4.1. Description of the Monitoring System Architecture

The proposed architecture for performance monitoring and achieving the zero-downtime objective is layered, ensuring a clear separation between the physical, processing, and decision-making levels.

At the foundation of the system lie the Sensory Nodes (vibration, temperature, and current sensors), which are physically connected to the critical points of the machinery. These are linked to an industrial Edge Gateway that functions as a local translator and processor. Data is transmitted via MQTT to a local or cloud-based Broker, which serves as the central hub for the information. From there, the data is ingested by the InfluxDB processing engine (for time-series storage) and visualized through Grafana [16].

4.2. Hardware Component Selection (Edge Computing vs. Cloud Computing)

The balance between edge processing and centralized cloud computing is essential for an efficient architecture. Edge components, such as industrial computers based on ARM or NVIDIA Jetson processors, are selected for their ability to run signal processing algorithms (FFT – Fast Fourier Transform) in real time. This local processing enables instantaneous anomaly detection and automated equipment shutdown in the event of imminent danger, without relying on internet connection latency. Cloud computing (AWS, Azure, or Google Cloud) is utilized for massive historical storage and long-term predictive analytics. Cloud platforms allow for the correlation of data from multiple factories or similar machinery to refine Machine Learning models. For Productica 2026, we propose the use of robust dual-ethernet gateways (to separate the IT production network from the OT network) and 'store-and-forward' local memory to prevent data loss during temporary network disruptions.

4.3. Data Flow: From Sensor to Dashboard

The data trajectory begins with high-frequency analog acquisition. For instance, an accelerometer can generate 10,000 samples per second. The Edge Gateway does not transmit all of this raw data to the Cloud, which would be inefficient, but instead calculates statistical metrics: the RMS value, Crest Factor, and the frequency spectrum.

These features are transmitted to the broker as MQTT messages. The visualization system extracts the data and displays it on dashboards accessible via mobile devices or shop-floor monitors. The dashboards are configured to display a machine 'Health Score', where values above 90 indicate an optimal condition, while values below 70 automatically trigger a work order within the maintenance system.

4.4. Cybersecurity in Industrial Data Transmission

Extended connectivity introduces cybersecurity risks that can compromise not only data but also the physical safety of operators and equipment. The ISA/IEC 62443 standard provides the methodological framework for protecting these environments [13]. The proposed system implements network segmentation into Zones and Conduits. A zone represents a logical grouping of assets (for instance, a CNC machine work cell) [11], while conduits are the secure channels through which these zones communicate. Security is reinforced by:

- Multi-factor authentication for dashboard access.
- End-to-end encryption of MQTT messages using TLS 1.2/1.3.
- The use of X.509 certificates for the unique identification of each industrial gateway.
- Implementing the 'Least Privilege' principle, granting applications and users only the minimum rights necessary for operation.

5. Case study / Practical implementation

5.1. Description of the monitored manufacturing process

The case study is conducted using the Factory I/O simulation environment and focuses on a palletizing line located at the End of Line (EoL) stage of a production line. This stage is responsible for receiving finished products, positioning them correctly, and organizing them on pallets for storage or shipment. Due to its critical position in the technological workflow, any unplanned downtime at the palletizing level leads to a bottleneck across the entire line, making it an optimal candidate for the implementation of IIoT solutions. Within the simulation, the palletizing line is equipped with five types of industrial sensors highlighted in Fig. 4-8, which are representative of real-world applications:

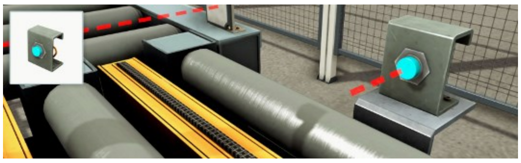

Fig. 4 Capacitive proximity sensor

Fig. 5 Inductive proximity sensor

Fig. 6 Through-beam photoelectric sensor

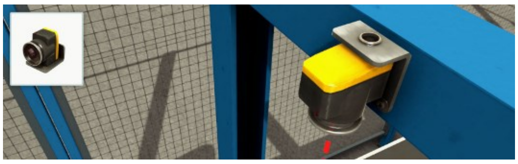

Fig. 7 Vision sensor

Fig. 8 Identification reader.

5.2. Implementation of the sensor network and configuration of IIoT nodes

The sensor network implemented on the palletizing line is designed to monitor the process at the End of Line stage in real time and to identify unplanned downtime. Specific discrete automation sensors are used, integrated at critical points of the technological workflow, with their configuration illustrated in the Fig. 9.

Inductive and capacitive proximity sensors are utilized to detect the position of mechanisms and the presence of products, contributing directly to the evaluation of the Availability and Performance components of the OEE metric. Through-beam photoelectric sensors (Light Arrays) enable the identification of bottlenecks and minor stoppages by monitoring the occupancy of transfer zones.

The vision sensor is used to validate the positioning of products on pallets, thereby impacting the Quality component of the OEE. Additionally, the RFID reader ensures the identification and traceability of pallets, facilitating the correlation of downtime events with specific batches or orders.

By correlating the data provided by this set of sensors, the system enables the quantification of downtime and the analysis of its impact on OEE, supporting the optimization of the palletizing process at the End of Line stage.

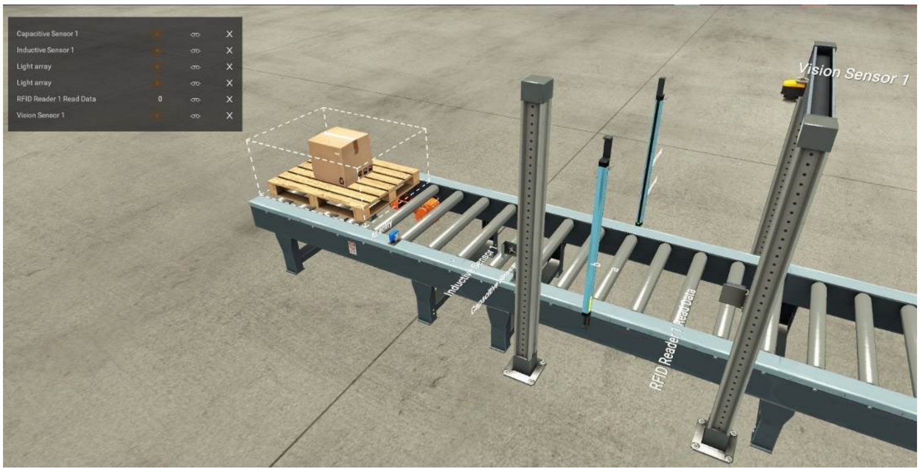

Fig. 9 Implementation of the IIoT sensor network on the End of Line

5.3. Data analysis: Predictive maintenance and anomaly detection

The data collected from the sensors integrated into the palletizing line are used to identify deviations from the normal operation of the process. Anomalies are highlighted by the absence of detection signals, prolonged occupancy of monitored zones, or incomplete operating cycles, situations associated with the occurrence of unplanned downtime.

The analysis of these events enables the delineation of downtime and the identification of recurrent patterns that may indicate the onset of issues before a major breakdown occurs. Thus, the collected data support the transition toward a predictive maintenance approach and contribute to enhancing the performance of the End of Line process.

5.4. Data visualization and alert generation

The practical implementation of the monitoring system is centralized in the dashboard shown in the Fig. 10, developed using the *Grafana* platform. This visualization tool provides an overview of the End of Line process performance, displaying critical indicators such as an OEE value of 82.3% alongside its availability, performance, and quality components. The near real-time monitoring of proximity, photoelectric, and vision sensors enables the rapid identification of bottlenecks (marked with the "BLOCKED" status) and operational anomalies. Additionally, the section dedicated to downtime analysis indicates a total of 39.7 minutes of downtime for the current shift, facilitating the transition from reactive to proactive monitoring by correlating events with their specific causes. The dashboard thus serves as an essential decision-support tool, demonstrating how collected data can be transformed into actionable insights to optimize production line efficiency.

Grafana is an open-source platform specializing in the visualization and analysis of time-series data, widely used in industrial and IIoT applications. It enables the creation of customized dashboards, the configuration of alerts, and integration with various data sources, providing an intuitive interface for monitoring process performance in near real-time.

In the absence of a real industrial infrastructure, simulated data were used, defined to reflect the typical behavior of the integrated sensors and the operation of an actual production line. The purpose of this approach is to demonstrate the role of a dashboard in performance monitoring and in the rapid identification of problematic areas within the End of Line process.

Fig. 10. IIoT data visualization for the End of Line process via the Grafana platform

The dashboard is structured to provide an overview of the process, including key indicators such as OEE, downtime events, and sensor status from the End of Line stage. The OEE metric is displayed against a target value, established for demonstrative purposes, allowing for a rapid evaluation of process performance [10]. The separate visualization of the availability, performance, and quality components facilitates the identification of factors contributing to the decline in overall efficiency.

The status of the proximity, photoelectric, and vision sensors, alongside the RFID reader, is displayed in near real-time through simple status-type indicators, enabling the operator to quickly notice any deviations from normal operation. Downtime events are highlighted both chronologically and as a distribution by cause, providing support for analyzing their frequency and impact on the palletizing process.

Although the data used are simulated, the dashboard clearly highlights the importance of centralizing and visualizing operational information. Through this interface, areas requiring interventions, process adjustments, or maintenance actions can be identified, supporting the transition from reactive to proactive monitoring [17].

Alert generation is achieved by defining thresholds for the monitored indicators, such as exceeding accepted downtime durations or dropping OEE below the target value. These alerts, illustrated at a conceptual level, demonstrate how an IIoT-based monitoring system can support rapid decision-making and contribute to reducing unplanned downtime and increasing operational efficiency in the End of Line stage.

6. Conclusions

This article analyzed the integration of IIoT sensors and a monitoring architecture focused on the End of Line stage, aiming to reduce unplanned downtime and increase operational efficiency. The case study targeted the palletizing process, considered critical for the continuity of the production workflow.

By utilizing the Factory I/O simulation environment, a palletizing line equipped with specific discrete automation sensors was modeled, and the resulting data were visualized within a Grafana dashboard. In the absence of a real industrial infrastructure, dummy data were used for demonstrative purposes to highlight the monitoring methodology for OEE and downtime metrics.

The obtained results emphasize the importance of centralizing and visualizing operational data in near real-time, facilitating the rapid identification of process deviations and areas with a major impact on performance. The proposed dashboard demonstrates the potential of IIoT solutions to support the transition from a reactive to a proactive approach, oriented toward preventing unplanned downtime.

In conclusion, the integration of IIoT sensors and the use of data visualization tools represent an essential step in adopting Industry 4.0 principles, even at the level of a single production stage, such as the End of Line. The presented solution is scalable and can be easily extended to other manufacturing processes or production lines.

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