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Utilizing Digital Twin to reduce fault diagnosis time of a reconfigurable machine built on the concepts of Industry 4.0 *

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Abstract—**Real-time implementation of Industry 4.0 concepts often emphasizes the integration of cross-platform technologies synchronized to manufacture one determined product. A digital twin replicates physical entities, adding a virtual model to visualize the real-time operations of a production plant. Such revolutionizing concepts of Industry 4.0 and emerging relevant technologies optimize the production efficiency in terms of swift fault detection of machines. To be specific, the production facilities that intend to deliver mass-customized products using reconfigurable machines often face extended downtime due to their complex operation. This innovative research work employs interoperable controllers that perform data-driven execution, receiving job requests from cross-platform social media to produce customized products (i.e., flavoured yogurt). Practically, when such machinery continuously manufactures customized products and stops working due to an unknown reason, a subject matter expert (SME) is often required to diagnose the error or detect faults in each domain. This leads to extended downtime, reducing Overall Equipment Effectiveness (OEE). In this paper, we explain the usage of digital twin technology built using Factory IO to reduce machine downtime, fasten fault diagnoses, and increase OEE, which ensures availability, performance, and quality.**

I. INTRODUCTION

In alignment with Saudi Arabia's Vision 2030, the Industrial Engineering Department (IED) at King Saud University (KSU) has taken key steps to embed Industry 4.0 concepts into its undergraduate curriculum. Early implementation included focused sessions and curriculum modules that introduced the core ideas of Industry 4.0, aiming to build a foundation for long-term technical competence.

To support this, educational strategies were adapted based on Jungmann's Research Cycle and Kolb's Learning Model, creating a framework where students are encouraged to apply theory to real-world industrial problems.

The Fourth Industrial Revolution has brought significant changes to the manufacturing sector by incorporating smart technologies into automation systems. Tools such as cloud-based data storage and digital twin models have become essential in modern production setups, allowing for better monitoring, control, and data-driven decision-making. Digital twin (DT) facilitates the continuous tracking of equipment performance, allowing for immediate detection of anomalies [1].

This paper utilizes Factory I/O to simulate a 3D model of a yogurt filling machine, providing a visual environment for testing control logic. The control logic was developed using CODESYS, a software platform compliant with the IEC 61131-3 international standard for programming Programmable Logic Controllers (PLCs).

To facilitate real-time data management and system interactions, Node-RED was employed, allowing for the comprehensive collection, processing, and display of operational data. This was cpmpleted by the development of a virtual representation of the yogurt filling machine on Raspberry Pi devices, thereby linking the physical asset with its digital model

Communication was further enhanced by integrating messaging platforms such as Telegram and WhatsApp, allowing users to send and receive production orders remotely. This setup ensured that the machine could be monitored and managed from different platforms, increasing flexibility and control.

Another key feature of this setup was the real-time, automatic temperature monitoring of the base yogurt and its flavored liquid, which allowed for immediate malfunction detection and rapid response, significantly minimizing downtime. A robust framework interlinks physical systems with their digital counterparts, enhancing predictive maintenance capabilities [2].

Overall, the project showed that integrating digital tools with physical systems speeds up technical problem-solving and provides more efficient operation. It highlights how smart technologies can play a practical role in improving modern manufacturing environments.

This paper presents a student-led ongoing research project that grew out of an Industry 4.0 orientation program, focused on building a smart production plant prototype. The project aimed to design and implement a modern, technology-integrated manufacturing system capable of producing a smart product, in line with key principles of Industry 4.0—such as digital connectivity, cloud-based manufacturing, and real-time data use.

To move beyond theoretical understanding and gain hands-on experience, the IED at KSU initiated the creation of this

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learning factory. This industrial prototype depicts a practical training environment, reflecting real-world industrial systems while offering students exposure to smart manufacturing tools and practices. At its core, the initiative represents a shift toward applying academic knowledge to solve real industrial challenges and encourages the development of scalable, practical solutions for the future of manufacturing.

II. SYSTEM DESCRIPTION

A. *Sequence of Operation*

The Yogurt Filling Machine (YFM), as illustrated in Figure 1, is an integrated automated system comprising a conveyor belt, a bottle-feeding mechanism, an optical scanning unit, and a centralized liquid dispensing head equipped with four precision nozzles for plain, blueberry, strawberry, and mango yogurt flavors. A FANUC LR Mate 200iC robotic arm is positioned to pick up the filled yogurt bottles from the conveyor belt and place them for the next packaging sequence. The system achieves full automation by utilizing a network of sensors strategically positioned across the machine to continuously monitor operational parameters. These sensors provide real-time feedback to a PFC from WAGO GmbH & Co a German based company, which performs high-speed signal acquisition and logic processing to actuate field devices accordingly. By coordinating all actuators based on input data, the PFC ensures synchronized operation, precise filling, and optimal throughput, minimizing human intervention and maximizing system efficiency.

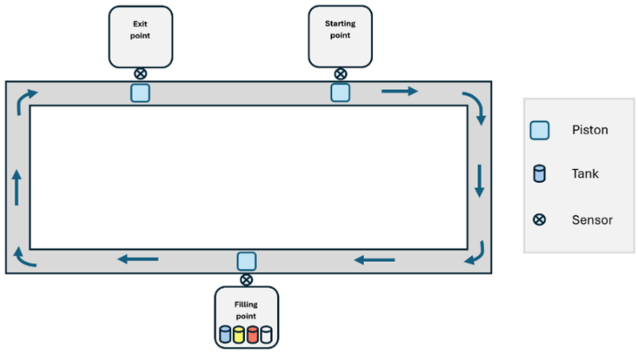


Figure 1 YFM process layout

The operational workflow of the Yogurt Filling Machine (YFM) integrates smart manufacturing principles inclusive of various software programs from Node-RED, CODESYS and FACTORY I/O.

The production process starts when the plant operator receives a job order from the client via WhatsApp or Telegram bots. This order is displayed on the Node-RED dashboard (Figure 2) executed in a Raspberry Pi, indicating the requested yogurt flavor and quantity. The operator must manually activate the process by pressing the START button.

Once activated, a photoelectric sensor checks for the presence of empty bottles and triggers the conveyor system. As bottles arrive at the filling station, a proximity sensor ensures they are accurately positioned using a 5/2 pneumatic valve. The filling process is then carried out automatically, blending yogurt with the selected flavor. This stage is managed by a WAGO PFC controller and closely monitored by sensors to maintain precision.

Temperature within the yogurt tanks is tracked in real-time using a wireless thermocouple sensor from NCD (National Control Devices, LLC, USA). The collected data is transmitted via Message Queuing Telemetry Transport (MQTT) to an Amazon Web Services (AWS) Internet of Things (IoT) gateway. Should any temperature deviations occur, an audible alert is triggered, and the system halts to prevent quality issues.

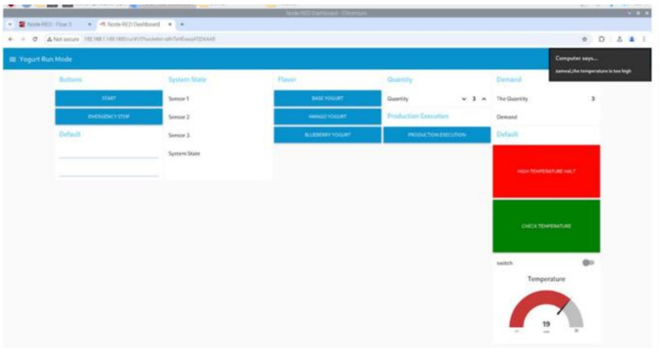


Figure 2 NodeRED dashboard

Upon filling, the bottles proceed down the conveyor line, where they are halted at a designated point by an additional sensor. Subsequently, a robotic arm precisely picks up the filled bottles and transfers them to the logistics area. This comprehensive setup integrates advanced automation, real-time data monitoring, and smart control technologies, thereby enabling efficient mass customization while adhering to Industry 4.0 standards for safety and flexibility.

A digital twin of the entire system was created using FACTORY IO software, where each input and output signal was carefully synchronized to replicate the behavior of the real-world process.

B. *Digital twin implementation*

By utilizing deep learning models, such as Autoencoders, DTs can analyze historical and real-time data to predict maintenance needs [1]. Factory I/O is a 3D industrial automation simulation software used to design, test, and validate control systems in a virtual environment. It supports integration with major PFC platforms, allowing real-time communication for control and monitoring. The software enables simulation of manufacturing lines, robotic arms, conveyors, sensors, and actuators, making it suitable for digital twin development, PFC programming, and system diagnostics. Factory I/O offers high ease of use, realistic 3D visualization, broad PFC compatibility, and cost-effective deployment for industrial training and automation design.

In this project, a digital twin of the yogurt filling machine is created using Factory IO for 3D simulation and integrated with Codesys software for real-time control, enabling operators to monitor system behavior, reduce manual interaction, and detect errors early. By simulating the machine virtually, operators can identify and resolve issues in real-time, improving operational efficiency, accuracy, and minimizing downtime. The implementation includes several steps:

- The conveyor system is represented by seven connected conveyor belts due to software constraints, as shown in Figure 3.
- Four tanks are added to represent the base yogurt and three flavor variants (strawberry, blueberry, and mango).
- A control panel is integrated to simulate the actual yogurt filling machine's control system.
- Three stop points are placed to simulate the machine's key control stages: the starting point, the filling point, and the endpoint.
- Sensors are positioned to ensure the presence of bottles at each stage: starting, filling, and ending.
- To overcome software limitations in simulating colored liquids, labels are used on the tanks to distinguish the yogurt and flavors, with the labels shown as small squares on top of the tanks (Figure 3).

Figure 3 A Virtual Model of YFM.

C. *Interfacing with Codesys software*

In this project, CODESYS was used as the primary programming and configuration environment for developing, deploying, and managing the PFC control logic. It played a critical role in integrating the virtual model built in Factory IO with the physical controller, specifically, the WAGO PFC to enable real-time system monitoring and control.

The configuration process was divided into two main stages: project setup and network configuration. The software interface then guided the setup of the control environment. The CODESYS Control Win V3 x64 runtime was launched to simulate PFC functionality on the host device, and the CODESYS Gateway was configured to detect and communicate with local and remote devices.

Following successful connection, an Ethernet Adapter was integrated to facilitate industrial network communication. This adapter supports standard communication protocols, enabling seamless data exchange between the Programmable Logic Controller (PLC) and external systems, including sensors, actuators, and simulation environments. A Modbus TCP Server device was then integrated under the Ethernet configuration. This server enables bidirectional communication between the PFC and third-party platforms, such as Node-RED, by allowing them to read from and write to PFC memory. This setup supported robust integration for data acquisition, process control, and external system interfacing over a TCP/IP network.

III. Problem Statement and Proposed Digital Twin Solution

The Yogurt Filling Machine (YFM) frequently encounters mechanical and connectivity issues, leading to significant delays in fault diagnosis. Human operators currently require an average of six minutes to manually verify each parameter using a checklist. This traditional inspection process, conducted at both the process and field layers, not only exacerbates downtime but also hinders the ability to respond promptly to dynamic production demands. Consequently, these inefficiencies severely impact OEE, overall operational performance and result in prolonged production delays.

To address these challenges, this project aims to implement a digital twin of the YFM using Factory I/O simulation, providing real-time monitoring and control of the physical system. The digital twin enables automated diagnostics and visualization of machine behavior, reducing manual inspection time by up to 75%. By integrating a WhatsApp-based interface connected to a Raspberry Pi 5, operators can directly submit production requests, specifying details such as flavor, size, and quantity, thereby streamlining the job-order process and reducing manual scheduling delays.

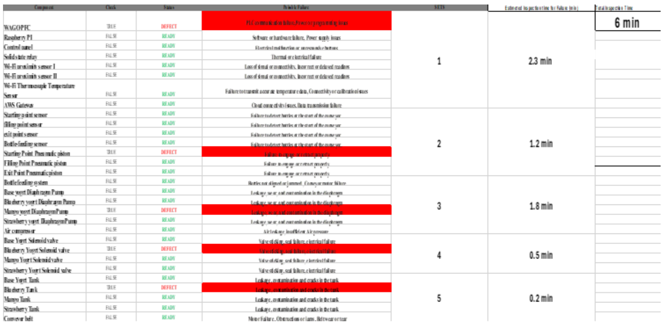
The system's real-time, predictive diagnostics will significantly minimize unplanned downtime by accelerating fault detection and automating the verification of critical components. This solution not only enhances system reliability but also optimizes machine performance, leading to greater operational efficiency and reduced costs. Ultimately, the integration of a fully automated fault detection and diagnostic system represents a key advancement toward Industry 4.0, improving both the flexibility and responsiveness of the production process.

A. *Checklist for fault diagnosis*

Initially, troubleshooting the YFM presented a somewhat disorganized process, with issues often leading to unsystematic checks of sensors, wiring, and valves. As familiarity with the system increased, a more systematic approach to problem diagnosis was adopted. To further streamline this process, a diagnostic checklist was developed, specifically focusing on components identified as most prone to failure.

This checklist provided multiple benefits: it reduced the time spent troubleshooting, provided a reference for future operators, and allowed us to collect valuable data. For example, we could track how long each component took to be inspected, how frequently each failed, and identify common issues.

The components were categorized into five functional groups, making it easier for operators to remember the inspection steps and complete them more efficiently. Based on our experience, we estimated that a full diagnostic of the system now takes around six minutes, significantly improving efficiency and minimizing downtime.



Component	Check	Status	Possible Failure	SETS	Estimated Inspection time for Failure (min)	Total Inspection Time
WAGO PFC	TRUE	DEFECT	PLC communication failure, Power or programming issues	1	2.3 min	6 min
Raspberry PI	FALSE	READY	Software or hardware failure, Power supply issues			
Control panel	FALSE	READY	Electrical malfunction or unresponsive buttons			
Solid state relay	FALSE	READY	Thermal or electrical failure			
Wi-Fi proximity sensor I	FALSE	READY	Loss of signal or connectivity, Incorrect or delayed readings			
Wi-Fi proximity sensor II	FALSE	READY	Loss of signal or connectivity, Incorrect or delayed readings			
Wi-Fi Thermocouple Temperature Sensor	FALSE	READY	Failure to transmit accurate temperature data, Connectivity or calibration issues			
AWS Gateway	FALSE	READY	Cloud connectivity issues, Data transmission failure			
Starting point sensor	FALSE	READY	Failure to detect bottles at the start of the conveyor	2	1.2 min	
filling point sensor	FALSE	READY	Failure to detect bottles at the start of the conveyor			
exit point sensor	FALSE	READY	Failure to detect bottles at the start of the conveyor			
Bottle-feeding sensor	FALSE	READY	Failure to detect bottles at the start of the conveyor			
Starting Point Pneumatic piston	TRUE	DEFECT	Failure to engage or retract properly			
Filling Point Pneumatic piston	FALSE	READY	Failure to engage or retract properly			
Exit Point Pneumatic piston	FALSE	READY	Failure to engage or retract properly			
Bottle feeding system	FALSE	READY	Bottles not aligned or jammed, Conveyor motor failure	3	1.8 min	
Base yogrt Diaphragm Pump	FALSE	READY	Leakage, wear, and contamination in the diaphragm			
Blueberry yogrt Diaphragm Pump	FALSE	READY	Leakage, wear, and contamination in the diaphragm			
Mango yogrt Diaphragm Pump	TRUE	DEFECT	Leakage, wear, and contamination in the diaphragm			
Strawberry yogrt Diaphragm Pump	FALSE	READY	Leakage, wear, and contamination in the diaphragm			
Air compressor	FALSE	READY	Air Leakage, Insufficient Air pressure			
Base Yogrt Solenoid valve	FALSE	READY	Valve sticking, seal failure, electrical failure	4	0.5 min	
Blueberry Yogrt Solenoid valve	TRUE	DEFECT	Valve sticking, seal failure, electrical failure			
Mango Yogrt Solenoid valve	FALSE	READY	Valve sticking, seal failure, electrical failure			
Strawberry Yogrt Solenoid valve	FALSE	READY	Valve sticking, seal failure, electrical failure			
Base Yogrt Tank	FALSE	READY	Leakage, contamination and cracks in the tank	5	0.2 min	
Blueberry Tank	TRUE	DEFECT	Leakage, contamination and cracks in the tank			
Mango Tank	FALSE	READY	Leakage, contamination and cracks in the tank			
Strawberry Tank	FALSE	READY	Leakage, contamination and cracks in the tank			
Conveyor belt	FALSE	READY	Motor Failure, Obstructions or Jams, Belt wear or tear			

Figure 4 Paper based checklist for fault diagnosis

The above Figure 4 diagnostics report presents the operational status of approximately 36 system components. Each entry includes details such as the component name, status check, current state, and any relevant health indicators or issues identified. Out of all entries, 25 components are reported as “READY,” indicating normal functionality. However, 11 components are marked with “ERROR,” pointing to specific failures within the environment. These include repeated issues like Packet Forwarding Engine (PFE) connection check failed due to proxy ping issue,” along with other critical failures such as “Local Postgres Database connection failure,” “PM process is not running,” and “Flink Job Manager/Task Manager is not reachable.” These errors collectively suggest problems related to network communication, service responsiveness, and internal process availability. The last three columns of the report—Estimated Log Collection Time, and Total Analysis Cycle Time—remain blank, indicating that either the data has not yet been gathered or is not required for this review cycle.

B. Technological constraints

The implementation of the digital twin architecture required stable and high-speed network connectivity, which posed a limitation due to restrictions on the lab’s Wi-Fi configuration. To ensure seamless communication between components, particularly between the Raspberry Pi 5 and the simulation/control environments—an external 5G router was deployed to provide a dedicated and reliable network connection, bypassing the firewall limitations of the institutional network.

Despite Factory I/O's effectiveness in simulating industrial automation environments, several constraints related to its component library were encountered during the modeling of the YFM:

- Limited Component Availability: The Factory I/O library lacks certain key components required to accurately replicate the YFM, such as bottles and certain mechanical elements. To overcome this, alternative components were used as substitutes. For instance, boxes were used in place of bottles to simulate the container flow within the system.

- Conveyor System Limitations: The actual YFM utilizes a continuous-loop conveyor belt. However, due to the absence of such a feature in Factory I/O, the conveyor was simulated using seven individual conveyor segments aligned consecutively to mimic continuous motion.

- Stop Mechanism Constraints: In the physical machine, the stopping mechanism operates via pneumatic pistons that raise a plate while the conveyor continues running. Factory I/O does not support this form of asynchronous control. As a result, the simulation required the conveyor to halt completely at predefined stop points, diverging from the real-world behavior where the conveyor runs continuously while bottles are selectively stopped.

IV. RESULTS AND EVALUATION

Predictive maintenance minimizes unexpected failures, leading to significant cost savings in repairs and downtime [3]. To facilitate the comprehensive implementation of the digital twin between Factory I/O and the YFM, the system was meticulously configured and programmed combining all the digital inputs and outputs. As depicted in Figure 5, the configuration within CODESYS provides a robust platform for defining and structuring all input and output parameters corresponding to the YFM.

Figure 5 PLC driver in Factory IO

Each I/O component was systematically assigned unique address and accurately linked to the respective elements in the Factory I/O simulation environment, as shown in Figure 5. This meticulous configuration process establishes a dynamic interface between the physical and virtual systems, with the PLC control unit acting as the central hub for data transmission and real-time process control. By ensuring precise mapping and synchronization between the physical assets and their digital representations, this integration enhances operational transparency, fault detection, and overall system performance. Whenever a failure or malfunction occurred in any input or output device, a red flag was automatically triggered to indicate the error. The data was then uploaded to an automated checklist that confirmed the system's readiness. If any error persisted, the operator would step in to identify and resolve the specific issue, ensuring no time was wasted on unrelated parameters. By optimizing maintenance schedules based on predictive analytics, manufacturers can maintain higher operational efficiency [4].

A. Automated Checklist for fault diagnosis

The adoption of digital twin technology has eliminated the need for traditional manual checklists by enabling real-time system monitoring and diagnostics. As shown in Table 1, this shift has led to significant improvements in efficiency, accuracy, and reliability. Unlike manual inspections, which are time-consuming, operator-dependent, and susceptible to human error, the digital twin operates autonomously, providing continuous monitoring and immediate alerts. Its embedded sensors detect internal or latent faults that manual methods often miss, and the system interprets data independently, reducing reliance on operator expertise.

Integrating Industry 4.0 and digital twin technologies enhances predictive maintenance by utilizing machine learning and advanced analytics for data fusion, enabling accurate failure diagnostics, prognostics, and optimized maintenance decisions, ultimately leading to cost-effective maintenance and improved predictive process intelligence [5]. Inspection records are automatically logged, supporting traceability and data-driven decision-making. The interface delivers a centralized view of system status, and the architecture allows seamless integration with Manufacturing Execution System (MES), Operational Risk Platform (ORP), cloud platforms, dashboards, and IoT systems. While manual checklists served as a practical foundation, the digital twin transforms inspections into a faster, smarter, and predictive process fully aligned with the goals of Industry 4.0.

TABLE 1 AUTOMATED CHECKLIST FOR FAULT DIAGNOSIS

S. No	***Feature / Aspect***	***Manual Checklist***	***Digital Twin***
1	Process Type	Operator-driven, manual process	Automated, real-time system-driven
2	Time Required	6 minutes per inspection	Instantaneous (real-time monitoring)
3	Human Error Risk	High risk of oversight, missed steps	Minimal risk, due to automated detection and consistent logic
4	Detection of Hidden Issues	Limited to visible symptoms	High detection capability, leveraging sensors for internal fault detection
5	Operator Skill Dependency	High dependency on operator expertise	Low dependency, system autonomously interprets data and identifies anomalies
6	Data Logging and Tracking	Manual entry or absent logging	Fully automated, data is logged and stored systematically
7	Fault Notification	Notifications after issue discovery	Immediate, system-triggered alerts in real time
8	Component Status Overview	Step-by-step, scattered information	Centralized, comprehensive system status overview
9	Ease of Use	Requires operator experience and time investment	User-friendly, minimal manual input required
10	Integration with Other Systems	Manual data entry for integration	Seamless integration with MES, ORP, cloud, IoT, and dashboards

This project involved the development and deployment of a digital twin for a (YFM), as depicted in Figure 6, to enable real-time monitoring and control. The digital twin was constructed using Factory I/O for 3D modeling and integrated with physical hardware components including Raspberry Pi module 4 and 5 units, a WAGO PFC controller, and a Wi-Fi thermocouple sensor. Communication between these components was established through the MQTT protocol, managed via Node-RED, with cloud connectivity provided by AWS IoT. This setup allowed physical processes such as filling operations, conveyor movement, and temperature variations to be accurately reflected in a virtual environment. A Raspberry Pi camera system was also incorporated for real-time image capture and monitoring.

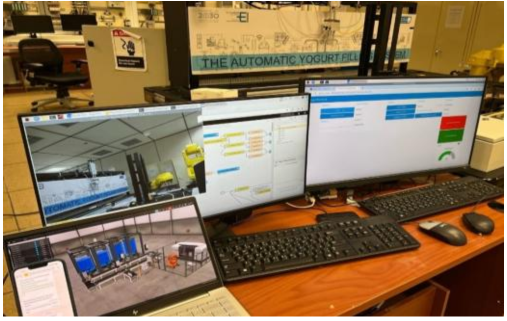


Figure 6 Validation of Digital twin

Synchronization between the digital model and the physical system was maintained continuously, with operational data displayed on a custom Node-RED dashboard. This interface enabled operators to control processes, monitor tank temperatures, and receive real-time alerts for faults or abnormal conditions. Temperature thresholds were enforced using automated alarms, and fault scenarios were simulated to assess system resilience. The virtual and physical systems responded in unison, ensuring rapid identification and resolution of issues. The implementation confirmed the effectiveness of the digital twin in enhancing operational visibility, supporting predictive maintenance, and aligning with Industry 4.0 smart manufacturing principles. DTs contribute to energy optimization and reduced emissions through proactive maintenance strategies [6]. Digital twins in Industry 4.0 enhance production systems by providing real-time control and strategic planning capabilities, which are crucial for automation in dark factories and cyber-physical systems [7].

V. CONCLUSION

The integration of core Industry 4.0 technologies is exemplified in this project through the development of a Digital Twin for a yogurt filling machine. This involved the incorporation of Factory I/O for 3D system modeling, CODESYS for programmable control logic, and Node-RED for data management and real-time visualization. This system architecture enables bi-directional communication between virtual models and physical components, facilitating real-time monitoring, dynamic process control, and advanced diagnostics. An example of simulated fault in the solenoid valve being indicated by the digital twin indicated (Fig7) the precision of fault digonses

Figure 7 Synchronization between real and virtual systems

Implementing a digital twin using Factory IO led to noticeable improvements in system responsiveness. Machine faults were identified and addressed more quickly, which helped minimize production delays. Extended periods of downtime have a direct impact on Overall Equipment Effectiveness (OEE), leading to declines in availability, performance, and quality. By integrating digital twin technology developed with Factory IO, the manual six-minute checklist traditionally used to diagnose faults was eliminated. The system enabled immediate identification of specific machine errors, allowing operators to bypass time-consuming diagnostics and proceed directly to fault correction. As a result, there was a measurable increase in Overall Equipment Effectiveness, with improvements observed in system availability, performance, and output quality. By strategically harnessing real-time decision-making, we’re strengthening enterprise-wide scalability. This foundation supports the launch of our initiative focused on AI-driven predictive maintenance and refined production optimization within a smart factory framework.

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