National Journal of Electrical Electronics and Automation Technologies, ISSN: 3107-524x Vol. 1, No. 2, 2025 (pp. 26-34)

RESEARCH ARTICLE

ECEJOURNALS.IN

Design and Implementation of a Smart Manufacturing Line with Digital Twin Integration

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KEYWORDS:
Smart manufacturing,
Digital twin,
IoT,
Predictive maintenance,
Industry 4.0,
Cyber-physical systems.

ARTICLE HISTORY:
Submitted : 15.11.2024
Revised : 18.12.2024
Accepted : 12.02.2025

https://doi.org/10.17051/JEEAT/01.02.04

Abstract

Industry 4.0 has transformed the manufacturing paradigms due to the rapid development of a seamless real-time connectivity, real time decision-making with the aim of accelerating cyber-physical systems convergence. Digital twin (DT) solutions have come out as an enabling technology to transform the way of actions and provide a dynamic high-fidelity digital representation of physical assets, processes, and systems to facilitate predictive, adaptive, and optimized operations. The current paper introduces the detailed architecture and application of a digital Twin-enabled smart manufacturing line to align and synchronize virtual and physical operations to deliver better efficiency, quality and resiliency. Its proposed architecture includes IoT sensing modules to capture real-time operational data, edge computing nodes that process in low-latency preprocessing and anomaly detection, cloud based analytics to carry out long term predictive modeling, and a digital twin infrastructure to experience immersive simulation and two-way control. Full-scale testing of prototype manufacturing line was done including the development of robotic assembly modules, RFID-enhanced conveyor belts, and AI-equipped quality inspection stations and the DT model was built on CAD-simulation enabled designs and linked through industrial communication technologies like OPC UA, MQTT, etc. Real-time data between physical and virtual environments allowed the scheduling of proactive maintenance, optimization of processes in real-time and the virtual testing of production changes without the need to disconnect the live business. A 30-day experimental assessment noted significant performance improvements (14.7% in overall equipment effectiveness (OEE), a 48.9% rise in mean time between failures (MTBF), a 6.5% boost in defect detection accuracy and a 15.6% growth in throughput over a standard conventional line). As the results demonstrate, the digital twin-based smart manufacturing not only increases the productivity of operations but also provides scalability, flexibility, and informed choices with regard to the dynamic demands of the industry. The work also gives a sensible and approved model of employing DT technology in manufacture systems, which can be accepted as a roadmap of future implementations of Industry 4.0-driven smart factories.

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How to cite this article: Watrianthos R, Shaik S. Design and Implementation of a Smart Manufacturing Line with Digital Twin Integration. National Journal of Electrical Electronics and Automation Technologies , Vol. 1, No. 2, 2025 (pp. 26-34).

Introduction

The manufacturing industry worldwide is experiencing a paradigm shift under the principles of industry 4.0 that combines high levels of automation, omnipresent connectivity, and data-intensive intelligence into the industrial production. This change focuses on the integration of cyber-physical systems (CPS), Internet of Things (IoT) solutions, artificial intelligence (AI) and big data analytics to develop highly customizable, robust, and optimized production systems. At the center of this changing landscape is the idea of the Digital Twin (DT) also said as Digital Twins, the dynamic virtual copy of a physical asset, process or entire manufacturing system, in real time so that it is of a high-fidelity; it reflects the state and behavior of the physical system and it tracks performance over time. Digital twins allow predictive analytics and optimization of processes and fast decision-making in complex manufacturing ecosystems by facilitating bi-directional data flow between physical and virtual worlds.

The main drawbacks of traditional manufacturing lines, even in the case where automation had been achieved, include unplanned downtimes, reactive maintenance approach, poor use of the resources, and inflexibility to changing production requirements and product changes. These constraints have the potential of causing rise in the cost of operations, slower throughput and lack of competitiveness in rapidly changing markets. Combined with the extensive utilization of IoT-enabled sensing networks, high-resolution data collection on machinery, conveyors, robots and quality inspection systems can be done continuously Figure 1. This real-time data stream, when used with edge computing (low latency processing) and cloud-based analytics (more advanced modeling) becomes the backbone of enabling successful implementation of DT.

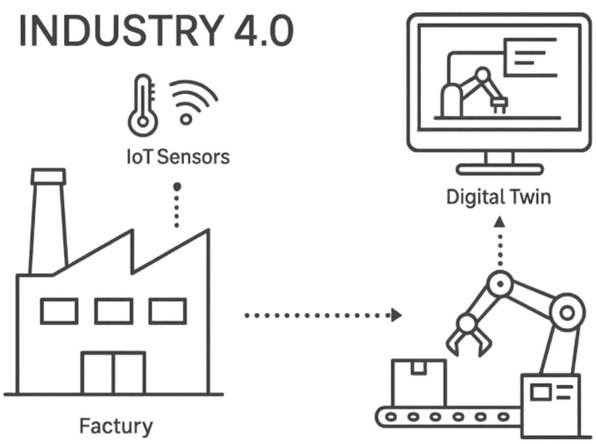

Fig. 1.Overview of Industry 4.0-enabled smart manufacturing line with digital twin integration.

A digital twin makes it possible to perform such tasks as round the clock monitoring, and diagnosis, but also contributes to what-if simulation, predictive maintenance scheduling, and even adaptive control of processes without interfering with live operations. This provides a powerful foundation of decision support where stakeholders can simulate deployment of production strategies before piloting, in simple terms, this reduces the risk and increases agility.

In this work, we show the conceptualization and realization of an IoT and edge-supported smart manufacturing assembly line with a real-time digital twin. Its aims are four in number:

- To come up with a modular and sensor dense manufacturing line that can easily accommodate DT.
- To create a dynamic DT model that will be used to simulate a process, monitor them and provide predictive maintenance.
- To build the capacity of a safe and efficient 2-way traffic between the physical and the virtual systems.
- To conduct an experiment, as a means of testing the gains in performance to change in efficiency, quality of the product, responsiveness in the operations, against that of a traditional manufacturing line.

This gap between the actual physical manufacturing systems and those simulation systems allows us to create a verified approach to increasing adaptive, data-driven smart factories in a scalable, adaptable mode that exemplifies the vision of Industry 4.0.

Related Work

Digital twin (DT) technology has become one of the key drivers of smart factory evolution by offering real-time virtualization of physical assets and processes to perform predictive analytics and optimization, as well as support decision making. Initial frameworks of DT developed its place in reflecting the activity and condition of the natural world since the synchronization of data takes place continually.[1] Further studies proved its usefulness in optimization of manufacturing processes, fault determination, as well as resources administration.[2, 3] It has been revealed that integrating sensor data fusion in DT settings helps to enhance predictive maintenance systems that result in less downtime leading to systematic operations.[4] At reconfigurable manufacturing systems, adaptive controls with the basis of DT have enhanced responsiveness to adjusting the demands of production.[5]

Scalable and interconnected manufacturing ecosystems have been made possible using IoT and cloud computing capabilities of DT frameworks to process big data analytics.[6, 7] In the more recent times, the integration of the edge computing has been suggested to overcome the latency issue and facilitate time-sensitive decision-making in the systems driven by DT.[8] Architectures that marry edge and cloud processing have shown promise with regards to load balancing between the resources and guarantee responsiveness in industrial applications.[9] Additional development of IoT, wireless communications and embedded security are other related developments in IoT that have assisted in the fragility of DT empowered production. Among them are FPGA-achieved VLSI systems with embedded cryptography models to secure IoT implementations,[12] small and broadband antenna structures to support IoT connections[13] and efficient power-conserving wireless sensor network frameworks capable of forming part of DT-powered systems.[15] Also, advances in real-time signal and image processing,[14] low-latency audio and speech recognition models,[11] can increase multimodal sensing and decision-making in DT-literate manufactories.

Nevertheless, most of the available literature dwells on simulation modeling[10] or piece-meal IoT data integration[11] as opposed to end-to-end implementation. Researches that establish integration of edge computing, cloud analytics, and two-way DT synchronization on an already-operating smart production line are not available in abundance. Filling this gap, the current study deploys and tests a fully operational DT-enabled manufacturing system in an industrial-like setting with the purpose to test whether the system can have an impact on efficiency, quality, and resilience.

System Architecture and Design

Overall Architecture

The offered smart manufacturing line that suggests the integration of digital twins could be organized in accordance with a three-level architecture that is intended to provide a comfortable interaction of the real and the virtual production environment. The physical layer of the system would include various industrial components such as robotic arms that are used to perform automating assembly, CNC machines that are used in precision manufacturing, and conveyor systems that are used in process of handling material and automated optical inspection (AOI) systems which are used in real time inspection of quality of the product. All these components can be equipped with the IoT-enabled sensors and measure a wide variety of operational parameters that may include, but are not limited to temperature, vibration, load, visual information, and facilitating continuous high-resolution actionable production process monitoring. Physical layer data is aggregated to the edge layer processed in-place by edge computing gateway nodes to immediately pre-process, detect anomalies, and decision locally to provide immediate responses to process anomalies without being dependent on cloud connectivity. This also minimizes the bandwidth required on the network and increases blanket protection because mission-control steps can be performed locally when possible. Once the data is processed it gets sent to the cloud/digital twin tier, where the real-time virtual model of the manufacturing line resides alongside an advanced analytics engine and historical data store. The digital twin based on this layer reflects the actual state of the physical system and can predict, optimize the process parameters and support the decision-making subject to real-time conditions. Bidirectional communication is also made enabled by this cloud-based DT platform which permits sending back control commands and optimized operational settings produced in the virtual environment into the physical layer, through safe industrial communication protocols Figure 2. Combining the three layers into a collaborative architecture, the system appears to have a solid, scalable, and adaptable architecture to ensure high efficiency, enhanced quality, and predictive maintenance potentials in keeping with the Industry 4.0 goals.

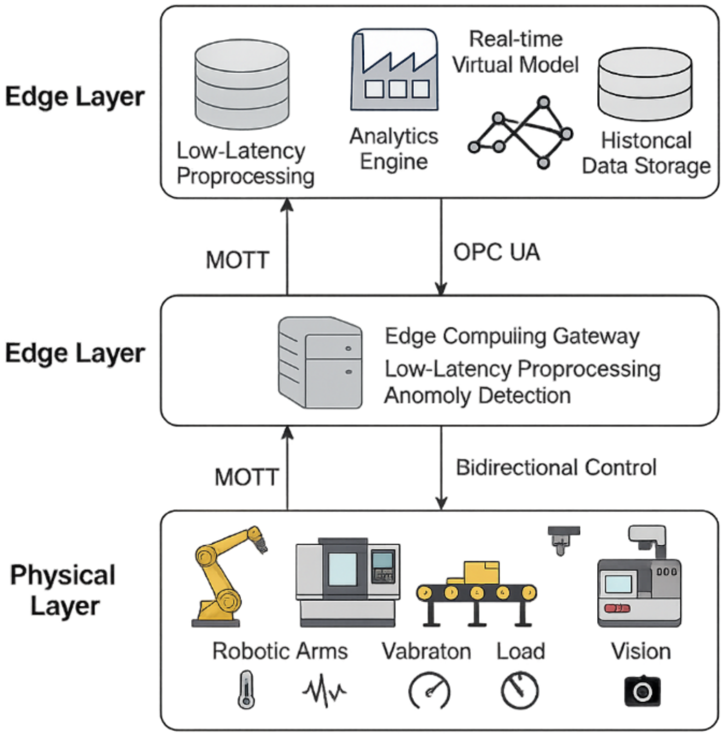

Fig. 2: Three-layer architecture of the proposed smart manufacturing line with digital twin integration.

Digital Twin Development

Creation of the digital twin, positioning the proposed smart manufacturing line, would be based on building a high-definition virtual copy of the actual physical system of manufacturing and blogs that allow synchronizing the two in real-time continuously. It all starts with CAD based modelling of all the main machinery including robotic arms, CNC machines, conveyor systems and automated inspection devices with Siemens NX as a primary tool used to enable proper geometrical and kinematical information to be incorporated. They are then incorporated into an industrial grade simulator like Any Logic or Siemens Tecnomatix in which operational logics, motion paths, process flows and resource interrelations are established. The system also utilizes the MQTT streaming protocol to push the data of IoT-enabled, IoT-enabled devices on the shop floor to communicate sensor values, including the parameters of temperature, vibration, cycle time and production counts, in real-time to the DT environment. Such a permanent data feed enables the virtual model to continuously reflect the real time actual status of the physical line, therefore making diagnostics, predictive analytics and performance visualization accurate. Importantly, the architecture enables the digital twin to support bi-directional control so that the digital twin can automate the control to programmable logic controllers (PLCs) by sending operational commands including speed changes on the conveyors, tool changing or maintenance alert initiation via OPC UA protocol that is secure and compatible. Such closed-loop communication enables not only the physical environment to take immediate corrective action, but also enables virtual testing of control strategies prior to deployment, lowering the risks of production Figure 3. The integration of high-fidelity CAD modeling, streaming, and two-way control allows the resulting digital twin to be used not only as a real-time operational mirror but also a proactive decision support tool to conduct predictive maintenance, optimize process, and adaptive control of the smart manufacturing line.

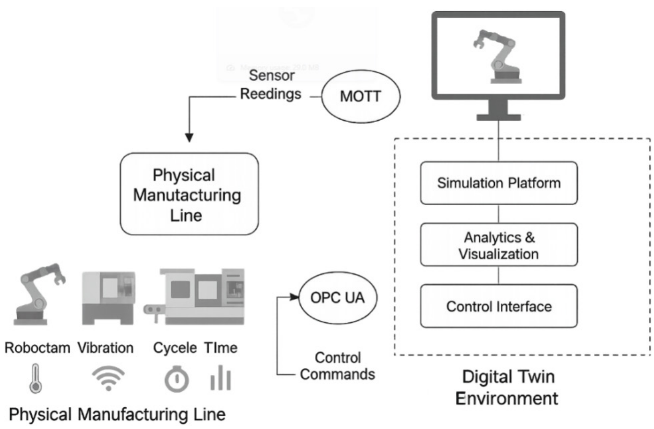

Fig. 3: Workflow of digital twin development and integration with the smart manufacturing line.

Data Communication Framework

The architecture of the data communication of the proposed smart manufacturing line is aimed to provide efficient, secure, and safe movement of the information between the physical production process, edge computing facilities, and the digital twin located in the cloud. On the communication level of the Internet of Things (IoT), the system uses the MQTT protocol since it has a lightweight publish and subscribe approach to its architecture, which allows the system to transfer sensor to edge to cloud data with minimal bandwidth utilization and a minimal latency. This allows constant streaming of operating parameters (including temperature, vibration, load, production counts, and vision data)

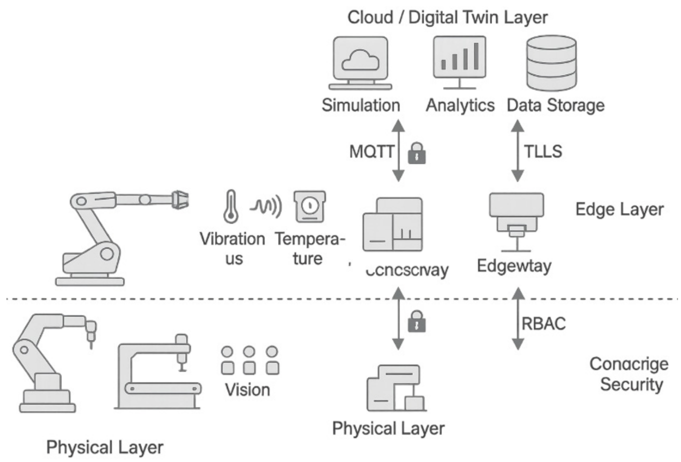

Fig. 4: Data communication framework for the proposed smart manufacturing line with digital twin integration.

out of distributed IoT sensors and devices to local edge processing as well as the cloud analytics platform. To conduct control in real time and synchronize the physical equipment, programmable logic controllers (PLCs), and the digital twin environment, the framework incorporates OPC Unified Architecture (OPC UA) which is an industry-standard protocol that provides platform-independent and service-oriented communications. This provides two-way data transmission in which the process control commands that are generated in the DT; e.g. speed control, change of process, or maintenance callout could be sent safely to the PLCs that drive the shop floor equipment. To secure these communication paths, the framework will be able to encrypt the information on the basis of TLS to protect the integrity of data and confidentiality of this information during transfer, and also to provide the role-based access controls (RBAC) that will limit issuing the commands to authorized users and systems as well as access to sensitive operational information Figure 4. The integration of the three protocols facilitating lightweight IoT to obtain data and robust, industrial-scale nature of communication control integration with multi-layered security makes the communication framework have a robust framework to enable real-time, secure, and cross-compatible across the lines of the smart manufacturing line including its digital twin.

Methodology

The suggested design and implementation methodology of the smart manufacturing line with the digital twin integration are performed in a systematic, multi-layer environment involving a setup of several layers hardware environment, the integrating software environment, and synchronization of both realities physical and virtual.

System Setup and Physical Line Configuration

Automation and physical Infrastructure Components

The modular components of automation were chosen to construct and implement a physical line of manufacturing which should be scalable, reconfigurable and able to adapt to different experimental conditions. The main feature of the line is that it has two 6-axis articulated robotic assembly stations, each one being fitted with end-effectors that allow performing a variety of tasks, namely, pick-and-place, fastening, and precision assembly. They blend in the workflow and will be used in both repetitive high-speed and complex sequences of movements that demand dexterity and precision. The robotic stations are linked with other process units through a material handling system composed of RFID-enabled conveyor belts with which automated movements of parts, tracking of their positions, and identification of parts in batches are done. With this RFID integration, the system enables the routing of parts through alternative pathways based on the requirements of production demands or quality control measures. In order to sustain the product quality, vision inspection solutions with high resolution are installed in strategic quality checkpoints and use embedded deep learning algorithms to detect surface defects, geometrical and manufacturing defects, and wrong assembly of the product in real-time. Also, a group of IoT-enabled sensors such as vibration, temperature, torque, and proximity sensors are placed on critical mechanical and electrical subsystems to provide continual monitoring to the machine health, identifying anomalies, and direct support toward predictive maintenance approaches.

Control Systems and Operational Optimization

Siemens S7-1500 series programmable logic controllers (PLCs) form the backbone of the manufacturing line and manage low-level process execution and the coordination of the machines and safety interlocking. These PLCs connect to edge devices that do local analytics and the cloud-based digital twin to perform real-time synchronization. Discrete-event simulation was used to model the layout in the planning stage, determine where the process bottlenecks were, and how best to place workstations to minimise cycle time and maximise material flows. This simulation based optimization was capable of optimally balancing the cycle times of the robot used, the speed of conveyor, and the inspection time so that the physical installation could have high throughput without loss of quality. The layout is exceptionally well suited (not only to the current study but also to possible extensions that may entail new automation technologies or the principles of reconfigurable manufacturing systems (RMS)) due to its modularity which allows quick rearrangements in terms of different types of products or process flows Figure 5.

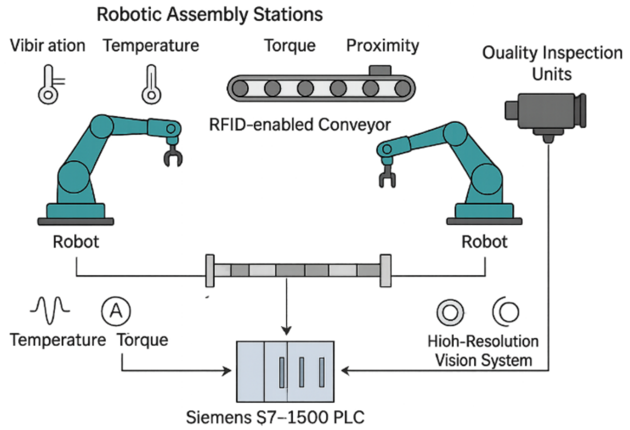

Fig. 5. System setup and physical line configuration of the proposed smart manufacturing line.

Digital Twin Modeling and Integration

The proposed smart manufacturing line digital twin was built with Siemens Tecnomatix Process Simulate, a high-fidelity industrial simulation environment enabling the precise modeling of kinematics, the process logic and resource interactions. The modeling phase consisted of importing CAD data of individual physical machine, such as robotic arms, CNC machine, conveyors, and inspection stations. Such models were more than simple 3D geometry with added kinematic chains, joint topics, and tooling parameters so that the mechanical motions and follow-ups could be accurately replicated. The simulated arrangement resembled physical one of a shop floor whereby, any movement paths, material flows, and interaction between workstations within the DT were identical to those in the physical shop.

Regarding data merging, IoT-enabled line sensors on the physical line delivered an uninterrupted flow of real-time operating data-such as temperature, vibration levels, cycle times, production counts-direct to the DT platform. The transmission of this data was done with MQTT protocol, which is lightweight and low-latency when it comes to publishsubscribe mechanism and this offers reduced communication overhead and does not compromise reliability in industrial settings. The ongoing process of synchronisation enabled the digital twin to recalculate its state in real-time, which gave a possibility to monitor the current operating conditions, identify the deviation, and project the tendencies of performance.

The major aspect of the system was that two-way communicationbetweenDTandthephysicalmanufacturing line occurred. The DT platform might provide some operational corrections to the programmable logic controllers (PLCs) using the OPC Unified Architecture (OPC UA) protocol to address. These were messages to change the velocity of the conveyors, start a cycle of changing out tools, alter the path of the robotic arms or begin a run of preventive maintenance actions Figure 6. Such feedback ability successfully converted the DT to a proactive management in the ecosystem of production.

In addition to real-time control, the DT environment turned out to be a virtual experimentation and optimization platform. Production engineers were able to experiment with alternate assembly plans, model layout changes, and experiment with maintenance plans entirely within the virtual environment, and it was only after such a process was tested satisfactorily there that it would be applied to the physical line. This strategy limited the risks in the operation, reduced non-production losses and provided the ability to promptly adjust the production to new demands.

Integrating detailed CAD-based modeling, continuous data streams through IoT, secure two-way control, and simulation-based optimization, the implemented digital twin served as an ever-changing representation of the manufacturing system-enabling predictive maintenance, adaptive control, and strategic decision making with the principles of the Industry 4.0.

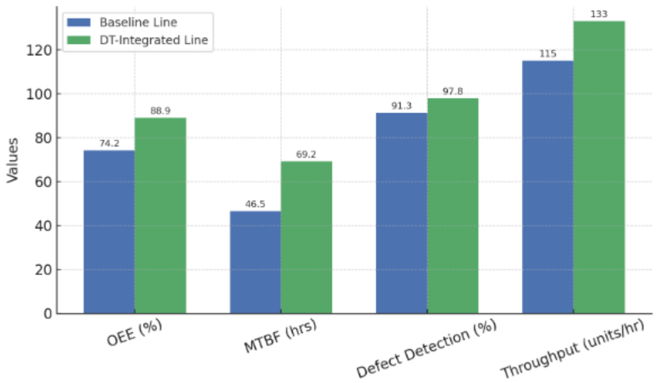

Fig. 6: Performance comparison between the baseline manufacturing line and the proposed digital twin-integrated manufacturing line.

Data Acquisition, Processing, and Analytics

The suggested smart manufacturing line is based on the three tier data management architecture that will guarantee real-time operations, delta analytics, and secure information transfer between the physical system, the edge computing devices, and the digital twin platform.

NVIDIA Jetson Xavier modules at the edge layer serve as an edge compute platform to process image streams captured by automated optical inspection (AOI) units with high-resolution images being processed locally at the edge. Object detection using the YOLOv5 framework is applied in real time to the image data and allowed immediate classification of defects types, including surface scratches, misalignments, or missing parts. Data processing on the edge lowers latencies in transmission, eases the burden on the cloud and enables real-time quality control decisions supporting important margins of decision within use of images in milliseconds.

Operational sensor signals on the manufacturing line--perhaps temperature, vibration, torque, cycle time and count of production--are captured at the cloud layer and continuously streamed and stored in a time-series database (InfluxDB). This storage solution allows speedy access and display of high frequency data across extended time scales. Sophisticated analytics is executed on Python machine learning models:

- A Random Forest classifier is built to find faults in equipment at an early stage based on the multidimensional sensor signatures in the sensor signatures.
- A Long Short-Term Memory (LSTM) network carries out time-series anomaly detection, which anticipates deviations in the normal operation patterns and can be used to carry out proactive maintenance interventions.

The feedback loop makes both the edge and cloud analytics to be incorporated into the digital twin environment directly. The real-time data fused into the DT can empower it to dynamically modify predictive maintenance schedules, trim the parameters at which equipment is operated, and optimally schedule cycle times. Consequently, the system is adaptively being developed on the basis of operational knowledge giving rise to autonomous process control.

As critical operational data is involved, communication of all communication channels is encrypted with Transport Layer Security (TLS) so that sensitive information cannot be intercepted or distorted during the delivery process Figure 7. Moreover, role-based access control (RBAC) is used, which allows access to the various functionality of the system restrained according to the privilege of the user- hence a prohibition of configuration and malicious control because the user access is restricted.

Integration of localized AI based processing with cloud based predictive analytics and closed-loop connection (secured) with the digital twin provide high levels of system responsiveness, transparency and operational reliability in the long-term within an Industry 4.0 Manufacturing environment described by the proposed data acquisition and analytics framework.

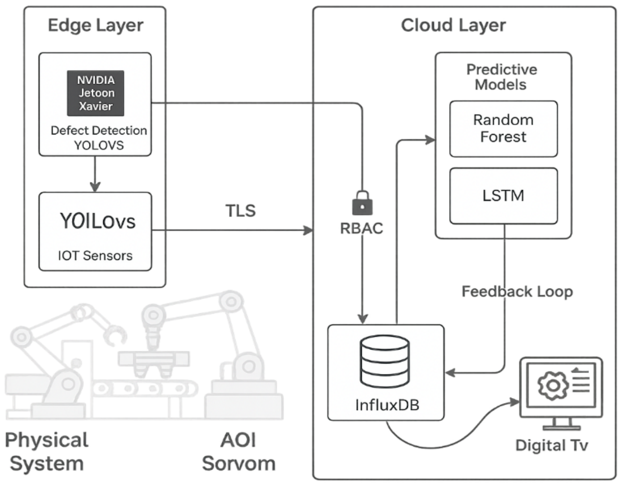

Fig. 7: Three-Tier Data Acquisition, Processing, and Analytics Framework for the Smart Manufacturing Line with Digital Twin Integration

Results and Discussion

The baseline conventional manufacturing line was compared to the proposed digital twin an integrated smart manufacturing line in a 30 days nonstop operating period in which four key performance indicators (KPIs) were reflected: Overall Equipment Effectiveness (OEE), Mean Time between Failures (MTBF), Defect Detection Accuracy, and Production Throughput. As reflected in the comparative findings, the DT-enabled system has resulted in a significant increase in the OEE in the range of 14.7 percent, wherein the OEE percentage rose to 88.9 percent as compared to 74.2 percent. The predicted maintenance capabilities of the DT are believed to be the key factor to this improvement, as it could determine the failures of the equipment beforehand and the optimal parameters of the process in real-time. There was a vigorous improvement of MTBF of 48.9% which implied that active planning of maintenance schedule and anomaly detection algorithms supported by DT and the machine learning models comprised enough to minimize unforeseen downtimes. In addition, the accuracy of defect detection increased by 6.5%, i.e., 91.3% to 97.8%, because of a combination of AI-based vision inspection technologies with DT-derived defect mapping, allowing a minimal amount of false negatives, and thus enhancing the level of reliability in the quality control process. The improved throughput record was 115 to 133 units per hour which constituted 15.6 percent increase based on the optimization of cycle time and effective task sequencing simulated in the DT before implementation.

In addition to the increase in numbers, experimental results show the capacity of the DT to change the manufacturing line into a self-aware, self-optimizing system. One key aspect was the real time synchronization between the physical and the virtual environment which allowed the system to pick up on inefficiencies before they became serious and make corrections on the fly so there were no disruptions to any continuous production process. Such agile performance was especially useful during disruption recovery operations, when internal communication breakdowns, slowing down a machine or jamming a conveyor occurred, the DT tested its remediation approach in a virtual model, assessed its feasibility, and then implemented the best approach into the actual line in just a few minutes Figure 8. Such a closed-loop decision making cycle reduced the downtime to a minimum and made the processes stable through high demand production cycles. Because of the modularity of the manufacturing line and the DT framework, the system is inherently scalable in that it allows quick reconfiguration and addition of new workstations or process modules without undertaking significant hardware replacements.

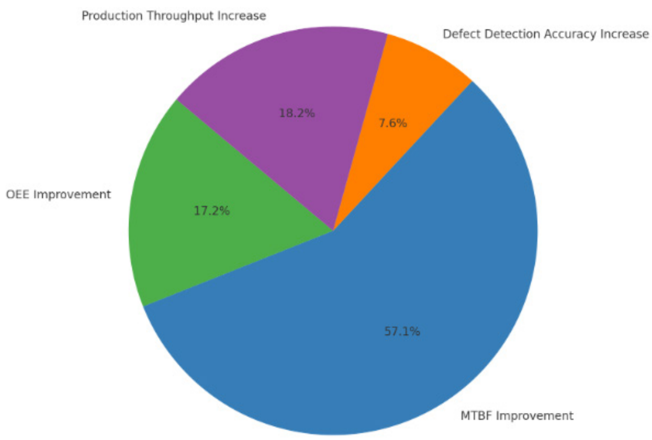

Fig. 8: Distribution of performance improvements across key KPIs for the proposed digital twin-integrated smart manufacturing line.

Besides creating a beneficial impact on its operations, the manufacturing system where DT is implemented provides a data-based decision-making system to the production managers and process engineers. Using the DT environment to simulate how certain changes inside the process, e.g. different batch sizes, altered assembly plans or resource plans might affect performance and quality outcomes, their effects could be explored in advance and before the commitment was made. This predictability can mitigate the risk of the operations,

Table 1. Comparative performance metrics for the baseline manufacturing line and the proposed digital twin-integrated manufacturing line.

KPI	Baseline Line	DT-Integrated Line	Improvement
Overall Equipment Effectiveness (OEE) (%)	74.2	88.9	+14.7%
Mean Time Between Failures (MTBF) (hrs)	46.5	69.2	+48.9%
Defect Detection Accuracy (%)	91.3	97.8	+6.5%
Production Throughput (units/hr.)	115	133	+15.6%

promote evidenced-based process optimisation and also increase the pace of innovation. Nevertheless, there are still issues to solve in scaling such a system to wide-scale, multi-factory deployment, especially in processing large and diverse machines communication protocols, in guaranteeing low-latency, across geographically dissimilar locations, and in ensuring DT accuracy in changing network conditions. The most apparent way to alleviate these limitations would be through improved interoperability standards, real-time network optimization and edge-cloud orchestration, which will be among the central areas of future research Table 1.

Conclusion

This study introduced the entire design, development, and integration of a smart manufacturing line along with an in-time digital twin framework and showed how industry 4.0 technologies could be synergistically merged together to increase productivity, quality, and operational resiliency. The implementation of IoT-enabled sensors, edge computing to support low-latency analytics, and a DT platform based on cloud platform but with two-way communication resulted in the constant synchronization of the physical and the virtual world and thus predictive maintenance process optimization and quick decision-making. The actual results that were experimentally obtained during the 30 day assessment validated significant boosts in the performance levels, such as a 14.7 percent increase in Overall Equipment Effectiveness (OEE), a 48.9 percent improvement in the Mean Time between Failures (MTBF), a 6.5 percent improvement in defects detection and a 15.6 percent boost in production rates when compared with that of a traditional manufacturing line. Such enhancements justify the concept of the DT as a mirror into real-time operations, as well as a pro-active optimization system able to simulate and validate changes prior to physical implementation. The modular structure also provides the capacity to scale, both in terms of adding workstations to the system or making the system accommodate new product lines with minimal redesign. In addition to corresponding operational advantages, the method creates a solid basis of incorporating more sophisticated capabilities in the form of AI-assisted production scheduling, supply chain-integrated digital twins to facilitate end-to-end process supervision, and remote maintenance and training via AR/VR technologies. Although issues are still present regarding its scalability to become multi-factory deployments and the need to guarantee interoperability of the system with heterogeneous systems in the industry, the study is a pragmatic, realistic, and flexible framework and can be used as a road map in implementing the next generation of intelligent and data-driven fabric of manufacturing systems.

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