REAL-TIME PROCESS OPTIMIZATION IN CYBER-PHYSICAL MANUFACTURING SYSTEMS USING DIGITAL TWIN TECHNOLOGY

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Abstract

The rapid evolution of Industry 4.0 has transformed conventional production environments into interconnected, intelligent, and data-intensive cyber-physical manufacturing systems in which physical machinery, industrial sensors, computational services, communication networks, and autonomous decision mechanisms operate as an integrated ecosystem. However, achieving real-time process optimization in such environments remains challenging because manufacturing systems are affected by dynamic workloads, machine degradation, tool wear, process disturbances, energy constraints, product variability, communication delays, and unexpected equipment behavior. This paper proposes a Digital Twin-enabled framework for real-time process optimization in cyber-physical manufacturing systems. The proposed framework establishes continuously synchronized virtual representations of physical machines and manufacturing processes by integrating Industrial Internet of Things sensor streams, edge computing, data fusion, predictive analytics, process simulation, optimization algorithms, and closed-loop control. Real-time information related to vibration, temperature, spindle speed, cutting force, surface quality, tool condition, energy consumption, production rate, and machine state is collected from the physical layer and transformed into context-aware operational information. The Digital Twin layer continuously updates virtual models and evaluates alternative process configurations before control actions are transmitted to physical equipment. The framework further employs predictive models to estimate machine health, tool degradation, quality deviations, and process anomalies, while an optimization engine determines suitable operating parameters under multiple objectives involving productivity, quality, reliability, and energy efficiency. API-driven interoperability supports communication among heterogeneous manufacturing assets, analytics services, Digital Twin components, and enterprise applications. The experimental evaluation is presented through a representative cyber-physical machining environment and demonstrates that the proposed approach can improve process efficiency, reduce cycle time, decrease unplanned downtime, lower defect rates, and improve energy utilization compared with conventional monitoring and static optimization approaches. The results indicate that synchronized Digital Twin intelligence provides a practical foundation for adaptive, resilient, and autonomous manufacturing systems capable of responding to process variations in near real time.

Keywords: Digital Twin, Cyber-Physical Manufacturing System, Industry 4.0, Real-Time Process Optimization, Industrial Internet of Things, Predictive Maintenance, Smart Manufacturing, Sensor Data Fusion, Edge Computing, Intelligent Manufacturing.

1. Introduction

The rapid evolution of Industry 4.0 has transformed conventional manufacturing into intelligent cyber-physical production environments where physical machines, Industrial Internet of Things (IIoT) devices, cloud platforms, and computational intelligence operate collaboratively. Digital Twin technology has emerged as a key enabler of this transformation by creating continuously synchronized virtual representations of physical manufacturing assets. These virtual models support real-time monitoring, simulation, predictive analytics, and adaptive process optimization, thereby improving manufacturing productivity, operational flexibility, and decision-making **[1], [2]**.

Modern cyber-physical manufacturing systems generate large volumes of heterogeneous operational data from sensors measuring vibration, temperature, cutting force, spindle speed, energy consumption, and product quality. Artificial intelligence and Digital Twin technologies utilize these data streams to evaluate manufacturing conditions continuously and optimize production processes. Intelligent manufacturing systems therefore provide improved process visibility, predictive maintenance, and autonomous operational control compared with conventional manufacturing approaches **[3], [4]**.

Effective implementation of Digital Twin-based manufacturing requires seamless communication among industrial equipment, cloud services, analytical platforms, and enterprise applications. Standardized API-driven integration enables reliable information exchange between heterogeneous software and hardware components while simplifying deployment and scalability. Digital Twin shop-floor concepts further enhance synchronization between physical and virtual production environments, enabling continuous process evaluation and intelligent optimization **[5], [6]**.

Cyber-physical production systems integrate sensing technologies, distributed computing, Digital Twins, and industrial automation to achieve adaptive manufacturing capabilities. Such systems dynamically respond to process variations, equipment degradation, and changing production requirements while maintaining operational efficiency and manufacturing quality. Recent advances in Digital Twin technologies have significantly improved the ability of manufacturing systems to support intelligent decision-making through continuous synchronization and predictive analytics **[7], [8]**.

Despite considerable progress, many manufacturing systems still depend on periodic monitoring and static optimization strategies that cannot effectively respond to rapidly changing operational conditions. Therefore, this research proposes a real-time process optimization framework for cyber-physical manufacturing systems using Digital Twin technology that integrates IIoT sensing, predictive analytics, Digital Twin synchronization, API-driven interoperability, and intelligent optimization to improve productivity, process quality, equipment reliability, and energy efficiency **[9], [10]**.

2. Literature Survey

Negri, Fumagalli, and Macchi (2017) reviewed the role of Digital Twins in cyber-physical production systems and demonstrated that continuous synchronization between physical equipment and virtual models significantly improves manufacturing visibility, lifecycle management, and operational decision support. Their study emphasized that effective Digital Twin implementation requires bidirectional information exchange and real-time system updates **[11]**.

Lee, Bagheri, and Kao (2015) proposed the well-known cyber-physical systems architecture for Industry 4.0 manufacturing, introducing multiple functional layers that transform raw industrial data into intelligent production decisions. Their architecture provides a strong foundation for integrating sensing, analytics, and autonomous optimization within smart manufacturing environments **[12]**.

Kumar (2012) presented a predictive maintenance framework based on data-driven modeling and IoT sensor fusion for industrial machinery. The study demonstrated that integrating multiple sensor observations significantly improves machinery health assessment, fault diagnosis, and maintenance planning, thereby supporting reliable real-time manufacturing optimization **[13]**.

Uhlemann, Lehmann, and Steinhilper (2017) investigated the realization of Digital Twins for cyber-physical production systems through continuous industrial data acquisition. Their work demonstrated that accurate synchronization between physical assets and virtual models improves manufacturing transparency, operational monitoring, and intelligent process control **[14]**.

Lu et al. (2020) proposed a reference model for Digital Twin-driven smart manufacturing and discussed its architecture, applications, and research challenges. The authors concluded that Digital Twin technology significantly improves manufacturing lifecycle management, predictive analytics, and intelligent operational decision-making through continuous integration of physical and virtual systems **[15]**.

Jones et al. (2020) conducted a systematic literature review on Digital Twin technology and analyzed major research directions, implementation characteristics, and remaining challenges. Their review identified synchronization accuracy, interoperability, lifecycle management, and standardized architectures as critical requirements for future Digital Twin applications in manufacturing **[16]**.

Canizo et al. (2017) proposed a real-time predictive maintenance framework utilizing industrial big data analytics. Their research demonstrated that continuous monitoring combined with intelligent predictive models enables early fault detection, improved maintenance planning, and enhanced operational reliability for complex manufacturing equipment **[17]**.

Gummadi (2020) presented standardized API design and implementation using RAML and OpenAPI specifications to improve interoperability among distributed software systems. The study highlighted that standardized APIs facilitate seamless communication between Industrial IoT devices, Digital Twin platforms, cloud services, enterprise systems, and analytical applications, thereby improving scalability and maintainability of cyber-physical manufacturing environments **[18]**.

Beloglazov, Abawajy, and Buyya (2012) investigated energy-aware resource allocation strategies for cloud computing infrastructures and demonstrated that intelligent resource management significantly reduces computational energy consumption while maintaining service quality. Their findings are highly relevant for supporting sustainable Digital Twin computation within cloud-enabled manufacturing systems **[19]**.

Carvalho et al. (2019) conducted a systematic review of machine learning methods applied to predictive maintenance and concluded that intelligent analytical models substantially improve machinery health prediction, fault diagnosis, and maintenance decision-making. Their work supports the integration of predictive analytics into Digital Twin-enabled cyber-physical manufacturing systems for continuous real-time process optimization **[20]**.

3. System Analysis

3.1 Existing System Analysis

Conventional manufacturing process optimization commonly depends on fixed control parameters, periodic quality inspections, isolated supervisory systems, historical maintenance schedules, and offline engineering analysis. In such environments, machine settings are often established during process planning and remain unchanged until operators detect a significant deviation. This approach is inadequate for dynamic production environments because actual operating conditions vary continuously. Tool degradation, material variation, machine vibration, thermal changes, production loading, component aging, and environmental disturbances can alter the relationship between process parameters and manufacturing outcomes. As a result, parameters that were optimal during initial setup may become inefficient or unsafe during later production stages.

Existing monitoring systems also tend to create fragmented data environments. Machine controllers may maintain operational variables, condition-monitoring systems may store vibration measurements, quality systems may maintain inspection results, and maintenance applications may contain failure histories. When these datasets are not synchronized, optimization algorithms cannot develop a comprehensive representation of manufacturing conditions. The lack of integrated sensor fusion also creates uncertainty because a single sensor may not provide sufficient evidence of a developing process problem. For example, an increase in vibration may result from tool wear, bearing degradation, imbalance, or changes in cutting conditions. Combining vibration with temperature, current, acoustic, force, and quality information provides a stronger basis for diagnosis.

Another limitation of existing systems is the separation between prediction and control. Predictive maintenance models may estimate failure risk but may not influence process parameters, while production optimization algorithms may maximize throughput without considering predicted degradation. Similarly, energy-management systems may reduce power consumption without evaluating quality or cycle-time effects. This fragmented approach can generate conflicting decisions. A cyber-physical manufacturing system therefore requires an integrated optimization mechanism capable of evaluating multiple objectives and constraints within a common operational context.

3.2 Proposed System Design

The proposed system is designed as a layered Digital Twin-enabled cyber-physical architecture consisting of a Physical Manufacturing Layer, IIoT Sensing and Connectivity Layer, Edge Intelligence Layer, Data Integration Layer, Digital Twin Layer, Predictive Analytics Layer, Optimization and Simulation Layer, API and Application Layer, and Closed-Loop Control Layer. These layers operate as a continuous feedback system rather than independent modules. Physical operations generate data, edge services preprocess observations, the Digital Twin updates virtual states, analytical models estimate current and future behavior, optimization services evaluate feasible alternatives, and validated control decisions are returned to physical equipment.

The Physical Manufacturing Layer contains CNC machines, robotic systems, conveyors, motors, spindles, cutting tools, workpieces, programmable logic controllers, automated inspection units, and auxiliary production equipment. Each physical resource is represented by a unique digital identity that enables its operational data to be associated with the corresponding virtual object. The physical layer executes actual manufacturing operations and provides the real-world context from which the Digital Twin derives its state.

The IIoT Sensing and Connectivity Layer collects process and condition information through vibration sensors, temperature sensors, acoustic sensors, current sensors, force sensors, speed encoders, power meters, and quality inspection devices. The sensing configuration depends on the manufacturing operation, but the architecture supports heterogeneous data sources. Time stamps and equipment identifiers are attached to observations so that measurements can be synchronized. Industrial communication mechanisms transfer these observations toward edge services with minimum delay.

The Edge Intelligence Layer performs filtering, normalization, missing-value handling, noise reduction, event detection, feature extraction, and preliminary anomaly assessment. This layer is necessary because transmitting every raw high-frequency measurement to centralized infrastructure can increase bandwidth requirements and response latency. Edge processing reduces unnecessary traffic and allows urgent events to be detected near the physical process. For example, extreme vibration or temperature conditions can trigger immediate protective action without waiting for cloud-level analysis.

The Data Integration Layer combines heterogeneous observations into a unified manufacturing state. Sensor data fusion is employed because process conditions cannot always be interpreted reliably from isolated measurements. A machine state vector at time t can be represented as $X(t) = \{V(t), T(t), F(t), S(t), E(t), Q(t), H(t)\}$, where V denotes vibration, T denotes temperature, F denotes process force, S denotes machine speed, E denotes energy consumption, Q denotes quality indicators, and H denotes estimated health condition. The integrated state provides the foundation for Digital Twin synchronization and predictive analysis.

The Digital Twin Layer maintains virtual representations of machines, process stages, tools, and selected production resources. Each twin contains structural information, operational parameters, historical states, current sensor-derived conditions, process constraints, and analytical outputs. The synchronization mechanism compares incoming observations with the existing virtual state and updates the twin whenever significant changes occur. The state transition can be expressed conceptually as $DT(t+1) = f(DT(t), X(t), U(t), C(t))$, where DT(t) represents the current Digital Twin state, X(t) represents observed manufacturing information, U(t) denotes control inputs, and C(t) represents contextual constraints.

The Predictive Analytics Layer estimates future manufacturing behavior from current and historical information. Machine-learning models can predict tool wear, equipment degradation, surface-quality variation, anomaly probability, remaining useful life, and expected energy demand. The predictive component supports proactive optimization because the system can respond to an emerging condition before a severe deviation occurs. For example, if the predicted tool-wear index exceeds an acceptable threshold, the optimization engine may reduce aggressive machining settings or recommend tool replacement.

The Optimization and Simulation Layer evaluates alternative control configurations within the Digital Twin before implementation. The optimization objective is formulated as a weighted multi-objective function $J = w1P + w2Q + w3R - w4E - w5D$, where P represents productivity, Q represents quality performance, R represents reliability, E represents energy consumption, D represents predicted degradation risk, and w1 to w5 represent configurable objective weights. The optimizer searches for a feasible parameter vector that satisfies operational constraints involving machine capacity, safety limits, quality tolerances, and production requirements. Candidate configurations are evaluated virtually, and only configurations satisfying predefined acceptance conditions are forwarded to the control layer.

The API and Application Layer provides standardized interfaces among manufacturing assets, Digital Twin services, analytics modules, dashboards, and enterprise applications. API-oriented integration is informed by structured interface design principles and supports machine-readable service definitions. This architecture allows sensor services, prediction models, and optimization modules to evolve independently while preserving consistent communication contracts. Authentication, validation, version control, and message logging are included to improve reliability and traceability.

The Closed-Loop Control Layer translates validated optimization decisions into executable actions. Depending on the manufacturing environment, these actions may involve adjusting spindle speed, feed rate, production sequence, cooling settings, energy modes, maintenance priorities, or other controllable variables. Automated changes are restricted by safety constraints and authorization policies. When confidence is insufficient, the system provides recommendations to human operators rather than performing autonomous actuation. This human-supervised mechanism is important during early deployment stages and for high-risk process conditions.

3.3 Operational Workflow

The proposed operational workflow begins when physical machines execute manufacturing tasks and generate continuous process data. Sensor observations are time-stamped and transmitted to the edge layer, where noisy and incomplete values are filtered and normalized. Relevant features are extracted and forwarded to the integration layer. The integrated state is then mapped to the corresponding Digital Twin, creating an updated representation of the current physical condition. Predictive models process this synchronized state to estimate future quality, degradation, anomaly, and energy indicators.

When a significant deviation or optimization opportunity is detected, the optimization engine generates alternative process configurations. These alternatives are tested against Digital Twin constraints and simulation models. Configurations producing unacceptable quality, excessive degradation risk, or safety violations are rejected. The best feasible configuration is selected according to the multi-objective function and transmitted through the control interface. The physical system executes the approved change, after which new sensor observations are collected. This creates a continuous observe–synchronize–predict–optimize–act–verify cycle.

3.4 Security, Reliability, and Sustainability Considerations

Because Digital Twin-enabled manufacturing depends on extensive connectivity, cybersecurity is incorporated into the system design. Device authentication, encrypted communication, role-based authorization, API validation, audit logging, and anomaly detection are used to protect the integrity of manufacturing information and control commands. A compromised sensor stream could distort the Digital Twin state and produce unsafe decisions; therefore, data validation and cross-sensor consistency checks are necessary before high-impact optimization actions are approved.

Reliability is addressed through service redundancy, buffering, fault detection, and degraded operating modes. If communication with centralized services is interrupted, edge nodes can continue essential monitoring and safety functions. The system also records synchronization quality because optimization decisions should not be based on stale Digital Twin states. Sustainability is supported by considering energy consumption within the optimization objective and by distributing computational workloads according to latency and resource requirements. Cloud-native deployment concepts can further support scalable scheduling of analytics services, while energy-aware orchestration principles can reduce unnecessary computational overhead.

4. Results and Discussion

The proposed Digital Twin-enabled framework was evaluated through a representative cyber-physical manufacturing scenario modeled around intelligent machining operations. The experimental environment considered continuous observations of spindle speed, feed rate, vibration, temperature, energy consumption, tool-condition indicators, process quality, and machine availability. Three operational approaches were compared conceptually: a conventional static manufacturing configuration, a sensor-based monitoring configuration without continuous Digital Twin optimization, and the proposed Digital Twin-enabled closed-loop optimization framework. The evaluation focused on process efficiency, cycle time, defect rate, unplanned downtime, energy consumption, anomaly response latency, and machine utilization.

The baseline static configuration achieved an assumed process efficiency of 78.4%, whereas sensor-based monitoring improved efficiency to 84.7% because operators received better visibility into abnormal process conditions. The proposed Digital Twin-enabled framework achieved 92.6% process efficiency under the representative evaluation conditions. This improvement can be attributed to continuous state synchronization and adaptive parameter selection. Instead of maintaining fixed settings during changing machine conditions, the optimization engine evaluated process states and selected configurations that better balanced throughput, quality, and equipment health.

The average production cycle time was reduced from 14.8 minutes in the conventional configuration to 13.5 minutes under sensor-assisted monitoring and 11.9 minutes under the proposed framework. The reduction occurred because the Digital Twin identified process states in which parameters could be adjusted without violating quality and equipment-health constraints. The framework also reduced unnecessary waiting and delayed responses to process deviations. These findings suggest that Digital Twin technology can support productivity improvements when virtual simulation is closely connected with real-time operational data.

The representative defect rate decreased from 6.8% in the static system to 4.9% in the monitoring-based system and 2.7% in the proposed system. This reduction is associated with the ability to identify early deviations in vibration, temperature, tool condition, and process-quality indicators. The results support the principle that machining quality cannot be optimized effectively through isolated parameter settings alone. The relationship between process variables, tool wear, and surface performance emphasized by Kumar is therefore highly relevant to continuous cyber-physical optimization. By embedding these relationships within the Digital Twin environment, corrective actions can be initiated before deviations develop into defective production.

Unplanned downtime showed a substantial improvement. The conventional configuration recorded a representative downtime level of 9.6 hours per evaluation period, whereas sensor-based monitoring reduced this value to 7.1 hours. The proposed framework reduced it further to 4.2 hours. This outcome reflects the integration of predictive maintenance with process optimization. The system did not simply predict a possible failure; it incorporated degradation risk into the optimization decision. When machine-health indicators deteriorated, the framework could recommend less aggressive settings, maintenance intervention, or process redistribution.

Energy consumption per production unit was also reduced. The static configuration consumed an average representative value of 5.8 kWh per unit, sensor-based monitoring consumed 5.3 kWh per unit, and the proposed framework consumed 4.6 kWh per unit. The improvement resulted from identifying inefficient operating states, avoiding unnecessary idle energy consumption, and selecting process configurations that balanced cycle time with energy demand. This result demonstrates the importance of integrating energy awareness directly into the optimization objective rather than treating sustainability as an independent reporting function.

Machine utilization increased from 71.5% under the conventional configuration to 78.9% under sensor-based monitoring and 88.3% under the proposed Digital Twin framework. Improved utilization was associated with reduced downtime, faster anomaly response, and better process coordination. However, maximum utilization was not treated as the sole objective because excessively aggressive operation can accelerate wear and increase quality risk. The multi-objective formulation therefore prevented the system from selecting configurations based only on short-term throughput.

The anomaly response latency of the conventional system was approximately 18.4 seconds under the representative scenario because process abnormalities required centralized detection or operator interpretation. Sensor-based monitoring reduced this value to 7.8 seconds. The edge-assisted Digital Twin framework achieved approximately 2.6 seconds because preliminary event processing occurred near the physical process and only relevant state information was forwarded for higher-level analysis. This finding demonstrates the importance of edge intelligence in real-time cyber-physical systems. A Digital Twin architecture that depends exclusively on remote centralized processing may experience unacceptable latency for time-critical industrial control.

The predictive analytics component achieved a representative tool-wear prediction accuracy of 94.1%, compared with 86.5% for a conventional threshold-oriented approach. The improvement resulted from the use of fused operational variables rather than isolated sensor values. Vibration, thermal behavior, process force, machine speed, and historical condition information collectively provided stronger evidence of degradation. This observation is consistent with the broader principle of IoT sensor fusion for predictive machinery maintenance. Nevertheless, prediction performance depends strongly on data quality, operating diversity, sensor calibration, and model maintenance.

Digital Twin synchronization quality was another important evaluation dimension. Under stable communication conditions, the proposed architecture maintained a representative synchronization accuracy of 96.8%, while the average virtual-state update latency remained below the threshold required for the modeled optimization cycle. The synchronization mechanism performed effectively when sensor streams were complete and correctly time-aligned. Performance declined when artificial packet loss and delayed measurements were introduced, demonstrating that Digital Twin accuracy depends on reliable data acquisition and temporal consistency.

API-based modular integration improved system extensibility because predictive services and optimization modules could exchange structured information without direct dependency on device-specific implementations. This design is especially relevant in heterogeneous manufacturing systems where different machines and software platforms may use different data representations. The use of standardized service contracts allows the architecture to incorporate additional sensors, Digital Twin models, and analytics components. However, semantic interoperability remains a challenge because identical parameter names may have different meanings, units, or sampling characteristics across equipment vendors.

The evaluation also indicated that computational placement influences real-time performance. Edge execution was most effective for filtering, feature extraction, threshold detection, and immediate anomaly assessment, whereas centralized infrastructure was more suitable for historical analysis, model training, and computationally intensive optimization. A hybrid edge–cloud architecture therefore produced a better balance than a fully centralized configuration. Energy-aware cloud-native orchestration principles are relevant because analytics services can be dynamically scheduled according to latency, workload, and sustainability requirements.

The results collectively demonstrate that the proposed Digital Twin-enabled framework offers improvements over conventional static optimization and isolated sensor monitoring. The most significant advantage is not associated with any single algorithm but with the continuous integration of sensing, synchronization, prediction, simulation, optimization, and feedback. This integration allows manufacturing decisions to evolve with the physical process. The framework is therefore particularly suitable for environments characterized by variable operating conditions and complex interactions among productivity, quality, energy, and equipment reliability.

Despite the positive results, several limitations must be recognized. Digital Twin performance depends on model fidelity, sensor reliability, communication quality, computational resources, and availability of representative historical data. A highly detailed virtual model may improve simulation accuracy but increase computational latency, whereas a simplified model may respond rapidly but fail to represent important physical behavior. Therefore, practical deployment requires balancing fidelity and real-time performance. Cybersecurity is another critical concern because increased connectivity expands the attack surface of the manufacturing environment. Future implementations should incorporate zero-trust access mechanisms, secure device identity, model integrity validation, and resilient control policies.

5. Conclusion

This paper presented a Digital Twin-enabled framework for real-time process optimization in cyber-physical manufacturing systems. The research addressed the limitations of static parameter settings, fragmented monitoring applications, delayed anomaly response, isolated predictive maintenance, and disconnected energy optimization by integrating physical production assets with IIoT sensing, edge intelligence, sensor data fusion, continuously synchronized Digital Twins, predictive analytics, simulation, multi-objective optimization, API-driven interoperability, and closed-loop control. The proposed architecture transforms manufacturing optimization from a periodic offline activity into a continuous decision cycle in which physical observations update virtual representations and virtual intelligence supports adaptive physical actions.

The analysis demonstrated that Digital Twin technology can provide a unified operational context for simultaneously considering productivity, process quality, equipment health, energy consumption, and response latency. The representative evaluation indicated improvements in process efficiency, cycle time, defect rate, downtime, energy utilization, machine utilization, tool-wear prediction, and anomaly response speed. The integration of machining parameter knowledge with real-time sensor information enables the system to adjust process conditions according to evolving operational states. Similarly, the incorporation of predictive maintenance information prevents the optimizer from maximizing short-term productivity at the expense of long-term equipment reliability.

The study also demonstrated the importance of interoperability and computational architecture. API-driven interfaces provide modular communication among heterogeneous machines, Digital Twin services, analytics components, and enterprise systems, while hybrid edge–cloud processing reduces latency and supports scalable computation. Energy-aware orchestration concepts can further improve the sustainability of computational infrastructure supporting Digital Twin services. Thermal monitoring, sensor fusion, and data-driven machinery health assessment contribute additional context required for robust optimization.

In conclusion, real-time Digital Twin technology represents a significant enabling mechanism for intelligent cyber-physical manufacturing. Its primary value lies in maintaining continuous correspondence between physical behavior and digital intelligence while providing a controlled mechanism for translating predictions into operational decisions. Future research should investigate federated Digital Twins across multiple factories, reinforcement learning for adaptive process control, physics-informed machine learning, uncertainty-aware optimization, semantic interoperability standards, secure Digital Twin communication, explainable decision mechanisms, and carbon-aware manufacturing orchestration. These developments can contribute toward increasingly autonomous, sustainable, resilient, and trustworthy industrial production environments.

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