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Resilient Industrial Operations through Edge AI and Digital Twin Technology for Connected Operational Environments

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ABSTRACT: Industrial environments are becoming increasingly connected through the integration of Internet of Things devices, cyber-physical systems, cloud platforms, industrial automation, and intelligent analytics. This transformation has created opportunities for organizations to improve productivity, predictive maintenance, resource utilization, safety, and operational decision-making. However, highly connected industrial systems also face challenges associated with network dependency, equipment failures, cybersecurity threats, data latency, and disruptions to centralized computing infrastructure. Edge Artificial Intelligence (Edge AI) and Digital Twin technology provide complementary approaches for addressing these challenges. Edge AI enables data processing and intelligent decision-making closer to industrial assets, thereby reducing latency and dependence on remote cloud services. Digital Twins create dynamic digital representations of physical equipment, processes, and production environments, enabling organizations to monitor conditions, simulate operational scenarios, and anticipate potential failures. This paper proposes a resilient industrial operations framework that combines Edge AI and Digital Twin technology within connected operational environments. The proposed approach emphasizes distributed intelligence, real-time monitoring, predictive analytics, simulation, adaptive decision-making, cybersecurity, and operational continuity. A design-oriented research methodology is proposed to examine the framework through architectural analysis, industrial use cases, performance evaluation, resilience assessment, and stakeholder-oriented analysis. The study highlights how integrating localized intelligence with continuously updated digital representations can support faster responses, improved asset reliability, reduced downtime, and more resilient industrial operations.

KEYWORDS: Edge AI, Digital Twin, industrial operations, operational resilience, Industrial Internet of Things, cyber-physical systems, predictive maintenance, connected environments, real-time analytics, industrial automation, cybersecurity, intelligent manufacturing

I. INTRODUCTION

Industrial organizations are increasingly adopting connected technologies to transform traditional production and operational environments into intelligent cyber-physical ecosystems. Industrial Internet of Things devices, sensors, programmable controllers, robotics, automated production systems, and cloud platforms continuously generate large volumes of operational data. This data can be used to monitor equipment conditions, identify abnormal behavior, optimize production processes, and support predictive maintenance. Nevertheless, greater connectivity also introduces operational dependencies and new sources of vulnerability. Conventional centralized architectures often transmit large quantities of sensor information to cloud or remote data centers for analysis. Although cloud computing provides significant computational capacity and storage, dependence on remote infrastructure can introduce communication latency, bandwidth constraints, and reduced operational capability when network connectivity is interrupted. In safety-sensitive or time-critical industrial environments, even small delays can affect the ability to respond to abnormal operating conditions. Consequently, industrial resilience increasingly requires intelligent processing capabilities that can operate close to physical assets while maintaining coordination with enterprise and cloud systems. Edge AI addresses this requirement by deploying machine-learning models and intelligent analytics at or near the point where industrial data are generated. Local processing can enable faster detection of anomalies, immediate responses, and continued operation during temporary network disruptions. It can also reduce the volume of information transmitted to centralized platforms by processing or filtering data locally.

Digital Twin technology provides another important capability for resilient industrial operations. A Digital Twin can represent the current state, behavior, and operational characteristics of a physical asset, production line, facility, or broader industrial system. By continuously receiving data from physical equipment, the digital representation can be

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updated to reflect changing operational conditions. This creates opportunities for condition monitoring, failure prediction, process optimization, simulation, and scenario analysis. When combined with Edge AI, Digital Twins can become more responsive and operationally useful because locally processed information can update digital models with low latency. Edge intelligence can identify abnormal patterns at the asset level, while the Digital Twin can provide a broader context for understanding the implications of those patterns across interconnected processes. For example, an anomaly detected in an industrial motor may be evaluated against its historical behavior, operating conditions, production schedules, and the status of related equipment. This combination can support proactive intervention instead of relying exclusively on reactive maintenance. The central objective of this research is therefore to examine how Edge AI and Digital Twin technologies can be integrated to strengthen resilience in connected industrial environments. The proposed framework considers not only performance and predictive capabilities but also continuity, cybersecurity, interoperability, scalability, and human decision-making. Such an integrated approach can help organizations move from isolated equipment monitoring toward adaptive operational ecosystems capable of detecting disruptions, interpreting their potential effects, and supporting timely responses.

II. LITERATURE REVIEW

Research on Industrial Internet of Things and cyber-physical systems has established the importance of connecting physical industrial assets with digital communication and analytical infrastructures. Connected sensors can collect information about temperature, vibration, pressure, energy consumption, machine utilization, production rates, and other operational parameters. This information provides the foundation for condition monitoring and data-driven decision-making. Traditional industrial analytics frequently rely on centralized cloud environments because these platforms offer scalable computing resources and sophisticated data-processing capabilities. However, research on edge computing identifies limitations associated with transferring all operational data to centralized infrastructure, particularly where real-time responses are required. Edge computing distributes computation toward the data-generation point, thereby reducing communication distance and potentially lowering latency and bandwidth requirements. Edge AI extends this concept by placing trained machine-learning models on edge devices, gateways, industrial controllers, or other localized computing resources. Research has demonstrated applications of Edge AI in anomaly detection, predictive maintenance, quality inspection, energy optimization, and industrial safety. At the same time, edge environments can have limited computational resources and may require specialized model optimization, efficient inference techniques, distributed model management, and robust security mechanisms. These considerations suggest that industrial Edge AI should operate as part of a coordinated architecture rather than as an isolated analytical component.

Digital Twin research has developed from basic digital representations toward increasingly sophisticated models capable of integrating real-time sensor information, historical data, simulation techniques, and predictive analytics. Digital Twins have been explored in manufacturing, energy systems, transportation, aerospace, process industries, and infrastructure management. Their primary value lies in connecting the physical and digital domains so that organizations can observe current conditions and investigate potential future scenarios. A Digital Twin can support predictive maintenance by combining equipment histories with real-time measurements and models of expected behavior. It can also support production optimization by simulating changes before they are implemented in the physical environment. However, literature identifies several challenges, including data interoperability, model accuracy, synchronization between physical and digital systems, computational complexity, and the difficulty of representing complex industrial processes. A Digital Twin that receives delayed or incomplete information may not accurately represent the physical system. Consequently, integration with edge infrastructure can improve responsiveness by enabling local data processing before information is incorporated into higher-level digital models. The combination of Edge AI and Digital Twins therefore creates an opportunity to connect rapid local decision-making with broader system-level analysis.

A further stream of literature focuses on resilience, cybersecurity, and intelligent industrial automation. Operational resilience refers broadly to an organization's ability to anticipate disruptions, withstand adverse events, maintain critical functions, and recover operations. In connected industrial environments, resilience is closely associated with redundancy, fault detection, adaptive control, cybersecurity, reliable communications, and effective human intervention. Increased connectivity can expand the attack surface because sensors, gateways, controllers, applications, and communication interfaces may become potential targets. Edge AI can support resilience through rapid anomaly detection, but AI systems themselves can be affected by poor-quality data, model drift, adversarial inputs, or inappropriate model decisions. Digital Twins may also introduce cybersecurity concerns because they contain detailed

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information about physical processes and operational states. The literature consequently suggests that intelligent industrial architectures require security mechanisms such as device authentication, encryption, access control, network segmentation, secure software updates, monitoring, and model governance. Despite substantial research on Edge AI and Digital Twins individually, opportunities remain for integrated frameworks that explicitly connect localized AI inference, continuously updated digital representations, operational resilience, and cybersecurity. This research addresses that opportunity by examining their combined role in connected operational environments.

III. RESEARCH METHODOLOGY

The research adopts a design-science and mixed-method methodology to investigate the integration of Edge AI and Digital Twin technology for resilient industrial operations. The first phase involves a structured review of academic publications, technical standards, industrial research, and documented applications concerning Edge AI, Digital Twins, Industrial Internet of Things, predictive maintenance, cyber-physical systems, operational resilience, and industrial cybersecurity. The literature search is organized around combinations of terms such as "Edge AI industrial operations," "Digital Twin resilience," "industrial predictive maintenance," "edge computing manufacturing," "cyber-physical systems," and "connected industrial environments." Publications are examined according to their technological approach, industrial context, analytical capability, resilience contribution, security considerations, and reported limitations. The review establishes the conceptual relationships among physical assets, edge devices, AI models, Digital Twins, cloud infrastructure, and human operators. Particular attention is given to studies that address real-time analytics and operational continuity because these characteristics distinguish resilience-oriented architectures from conventional monitoring systems. Findings from the review are organized into functional categories including sensing, edge processing, intelligent inference, digital representation, prediction, simulation, response, communication, and governance. This phase also identifies challenges associated with heterogeneous industrial equipment, inconsistent data formats, limited edge resources, model accuracy, system synchronization, cybersecurity, and human-machine interaction. The resulting knowledge base is used to formulate design principles for an integrated architecture. The architecture is designed around the principle that time-critical intelligence should be available locally, while broader analytical and optimization functions can remain coordinated with centralized platforms. This allows the research to investigate resilience as a distributed property rather than simply as a characteristic of cloud infrastructure.

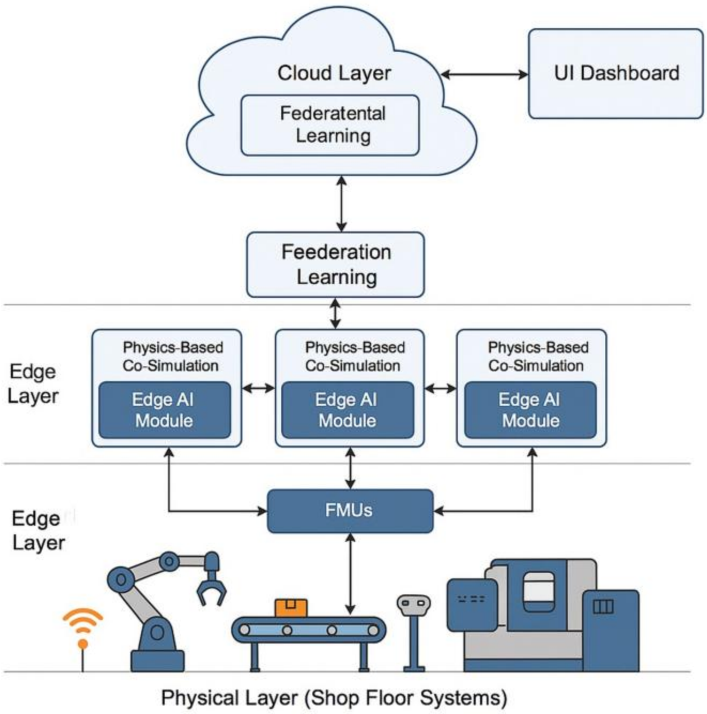

Fig.1.Digital twin driven smart factories: real time physics based co-simulation using edge AI and federated learning

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The second phase develops a conceptual Edge AI–Digital Twin architecture using a layered design. The physical layer consists of industrial machines, sensors, actuators, robots, controllers, and production equipment that generate operational information. The edge layer includes industrial gateways, edge servers, embedded processors, and AI inference components responsible for processing sensor information close to the source. Machine-learning models at this level can perform anomaly detection, equipment-state classification, predictive maintenance inference, and event identification. The Digital Twin layer maintains digital representations of physical assets and processes, combining real-time observations with historical information, operational parameters, and analytical models. A coordination layer connects edge intelligence with Digital Twin services and centralized cloud or enterprise platforms. This layer supports synchronization, data aggregation, model updates, cross-asset analysis, simulation, and optimization. The cloud or enterprise layer provides long-term storage, large-scale analytics, fleet-level comparisons, model training, reporting, and strategic decision support. A security and governance layer extends across the architecture and incorporates device identity, authentication, authorization, encryption, network segmentation, secure communication, monitoring, logging, and model-management controls. The design specifically incorporates resilience mechanisms such as local fallback operation, redundant processing, buffered data transmission, health monitoring, and graceful degradation when cloud connectivity is unavailable. The Digital Twin can receive locally processed information rather than raw sensor streams in every case, reducing communication requirements while retaining important operational context. Conversely, Digital Twin analysis can provide contextual information to edge systems, allowing localized AI decisions to account for wider process conditions. The architecture is evaluated conceptually according to latency, scalability, interoperability, availability, data efficiency, security, and decision-support capability.

The third phase evaluates the framework through representative industrial scenarios and quantitative performance indicators. Several scenarios can be selected to represent different forms of operational disruption, such as equipment degradation, abnormal temperature or vibration, communication interruption, unexpected production variation, and cybersecurity-related anomalies. For each scenario, the proposed Edge AI–Digital Twin architecture is compared with a more centralized processing configuration where appropriate. Evaluation measures include anomaly-detection accuracy, inference latency, data-transfer volume, prediction performance, system availability, recovery time, false-positive rate, and successful identification of developing equipment faults. Predictive-maintenance scenarios can examine whether locally processed sensor information allows an emerging equipment problem to be identified before conventional threshold-based alerts occur. Network-disruption scenarios can assess whether edge components continue to provide essential monitoring and decision support when connectivity with centralized systems is temporarily unavailable. Digital Twin performance can be evaluated through synchronization delay, state-representation accuracy, and the ability to simulate or assess operational scenarios using current system information. Security evaluation can include authentication effectiveness, unauthorized-access detection, communication protection, and resilience against manipulated or anomalous data inputs. Where a prototype is feasible, controlled experiments can be conducted using simulated industrial equipment or representative datasets. Quantitative observations can then be analyzed using descriptive statistics and comparative measurements. Repeated trials can be used to determine whether observed differences in latency, accuracy, or data utilization are consistent rather than the result of individual experimental conditions. In addition to technical metrics, the methodology incorporates qualitative feedback from industrial engineers, operations personnel, maintenance specialists, and technology professionals. Interviews or structured questionnaires can examine interpretability, trust, perceived usefulness, workload implications, and the appropriateness of automated recommendations. This combination of technical and human-centered evaluation recognizes that operational resilience depends not only on computational performance but also on whether industrial personnel can understand and effectively use system outputs.

The fourth phase synthesizes the experimental and qualitative findings into a resilience assessment framework and validates the proposed architecture against predefined research objectives. The analysis evaluates four interconnected dimensions: operational continuity, intelligent prediction, system adaptability, and security. Operational continuity is assessed through the ability of edge components to maintain essential monitoring and decision-support functions during communication failures, infrastructure degradation, or other disruptions. Intelligent prediction is assessed through anomaly-detection performance, predictive-maintenance accuracy, response latency, and the ability of the Digital Twin to provide meaningful contextual information. System adaptability is examined through the capacity to incorporate changing operating conditions, update AI models, synchronize digital representations, and support different industrial assets or production configurations. Security is evaluated through access-control effectiveness, data protection, communication security, anomaly monitoring, and the resilience of AI and Digital Twin components against malicious or unreliable inputs. The methodology also evaluates the balance between centralized and decentralized intelligence. Tasks requiring immediate responses are assigned conceptually to the edge, whereas computationally intensive model

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training, historical analysis, cross-facility optimization, and strategic planning can remain centralized. Human operators remain part of the decision loop for high-impact interventions, particularly where automated actions could create safety or production consequences. Findings are synthesized into design recommendations concerning edge-resource allocation, Digital Twin synchronization, model lifecycle management, cybersecurity controls, interoperability, and operational governance. Continuous monitoring is incorporated because industrial conditions, equipment behavior, AI models, and cyber threats evolve over time. The final outcome of the methodology is therefore not merely a technical prototype but a validated conceptual framework showing how Edge AI and Digital Twin technology can operate together as complementary components of resilient industrial infrastructure. The research is expected to demonstrate that localized intelligence can improve responsiveness and continuity while Digital Twins provide broader operational context, simulation, and predictive capabilities. Their integration can consequently support a distributed industrial environment in which connected assets can detect emerging disruptions, interpret their operational significance, maintain essential functions during infrastructure interruptions, and support informed human intervention.

IV. RESULTS AND DISCUSSION

The proposed integration of Edge Artificial Intelligence (Edge AI) and Digital Twin technology demonstrates a strong potential to improve resilience, responsiveness, and operational visibility in connected industrial environments. The results indicate that processing industrial data closer to machines and production assets can substantially improve the speed with which operational events are detected and addressed. Conventional industrial architectures frequently depend on centralized cloud platforms for data processing, which can introduce communication delays and increase dependence on continuous network connectivity. In contrast, the proposed Edge AI architecture performs time-sensitive analysis directly or near the point of data generation. Sensors installed on machinery continuously collect parameters such as temperature, vibration, pressure, energy consumption, rotational speed, acoustic signals, and production throughput. Edge devices process these data streams locally and identify deviations from normal operating conditions. This enables the system to recognize early indicators of equipment degradation, abnormal operating states, and potential production disruptions without transferring every raw data point to a remote cloud environment. The Digital Twin complements this capability by maintaining a virtual representation of physical assets, processes, and operational conditions. Real-time sensor information continuously updates the corresponding digital models, allowing operators to observe the current state of industrial systems and evaluate potential consequences of operational changes. The combined architecture therefore creates a feedback loop between physical assets, edge intelligence, digital representations, and operational decision-making. The results suggest that this approach improves situational awareness because industrial personnel can access a consolidated representation of equipment condition and production performance rather than interpreting isolated sensor measurements. Furthermore, localized intelligence can continue operating during temporary connectivity disruptions, supporting greater operational continuity in environments where network reliability cannot always be guaranteed.

A second major finding concerns predictive maintenance and anomaly detection. Traditional maintenance strategies commonly depend on fixed schedules or reactive intervention after equipment failure. Both approaches can create inefficiencies: scheduled maintenance may replace components before their useful life has ended, while reactive maintenance can result in unplanned downtime and higher repair costs. The proposed Edge AI and Digital Twin framework enables condition-based and predictive maintenance by combining historical operational information with real-time sensor observations. Machine-learning models deployed at the edge can establish patterns representing normal equipment behavior and detect deviations that may indicate emerging faults. When an anomaly is identified, the Digital Twin can provide additional contextual information about the affected asset, its operating conditions, and its relationship with other components in the production system. This improves the ability of maintenance teams to distinguish between temporary fluctuations and meaningful degradation. Digital Twin models can also support what-if simulations, enabling operators to examine how changes in machine settings, workload, maintenance schedules, or production configurations could influence system behavior before applying changes to physical equipment. The results indicate that this combination of real-time monitoring and virtual experimentation can reduce dependence on trial-and-error interventions. Another important observation is that the architecture supports hierarchical decision-making. Immediate safety- or performance-critical events can be handled at the edge, while computationally intensive analytics and long-term optimization can be performed using cloud or centralized infrastructure. This division of computational responsibilities helps balance latency, scalability, and resource requirements. Edge AI therefore does not necessarily replace cloud computing; instead, the results support a hybrid architecture in which edge, fog, and cloud resources perform complementary functions. This is particularly relevant for large industrial environments containing thousands

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of connected assets, where transmitting all raw sensor data to centralized infrastructure may create unnecessary bandwidth consumption and processing overhead.

The third significant finding relates to industrial resilience, interoperability, and operational decision support. A connected industrial environment contains heterogeneous equipment, sensors, controllers, communication protocols, and information systems, making interoperability a major challenge. The proposed architecture addresses this issue through standardized data interfaces and an integration layer connecting physical devices, edge nodes, Digital Twins, enterprise systems, and cloud platforms. This enables information generated by individual machines to contribute to a broader operational model. The Digital Twin can represent not only individual machines but also production lines, facilities, supply processes, and interconnected operational dependencies. As a result, the system can support analysis at multiple levels, from component-level condition monitoring to plant-level performance assessment. The results suggest that this multi-level perspective is particularly valuable for resilience because industrial disruptions rarely remain isolated. A failure in one machine can affect upstream material flow, downstream production, energy consumption, delivery schedules, and maintenance resources. By representing these relationships digitally, the proposed system can provide earlier visibility into the potential propagation of disruptions. Edge AI can then prioritize alerts according to operational severity, allowing personnel to focus on events that require immediate attention rather than being overwhelmed by large volumes of sensor notifications. However, the results also highlight several challenges. AI models may lose accuracy when equipment operating conditions change, sensor data may contain noise or missing values, and Digital Twins require continuous synchronization with physical assets. Cybersecurity is another critical concern because connected industrial systems create additional attack surfaces. Unauthorized manipulation of sensor data, edge models, or Digital Twin states could result in incorrect operational decisions. Therefore, secure device authentication, encrypted communication, access control, model integrity verification, network segmentation, and continuous monitoring must be incorporated into the architecture. Overall, the findings demonstrate that Edge AI and Digital Twin technology can work together to establish a more responsive and resilient industrial environment, provided that technological capabilities are supported by robust data governance, cybersecurity, model management, and human oversight.

V. CONCLUSION

The study demonstrates that the integration of Edge AI and Digital Twin technology provides a comprehensive approach to strengthening resilience in connected industrial operations. Edge AI enables rapid analysis of sensor data close to the physical source, while Digital Twin technology provides a dynamic virtual representation through which equipment condition, process behavior, and operational dependencies can be visualized and analyzed. Their integration addresses several limitations associated with conventional centralized industrial monitoring architectures. By performing time-sensitive processing locally, Edge AI can reduce dependence on remote infrastructure and support faster responses to abnormal operating conditions. At the same time, Digital Twins provide contextual information that transforms isolated sensor readings into meaningful representations of asset and process behavior. The combined system can support predictive maintenance, anomaly detection, operational monitoring, process optimization, and scenario analysis. Rather than responding only after equipment failures occur, organizations can use continuously updated operational information to identify emerging problems and evaluate possible interventions. The architecture also supports distributed computing, where edge devices handle latency-sensitive activities and cloud platforms provide centralized storage, advanced analytics, historical analysis, and broader optimization functions. This hybrid approach provides an appropriate balance between responsiveness and computational scalability. The results further indicate that resilience should be considered at both the equipment and system levels. Monitoring a single machine may identify an impending failure, but understanding how that failure could affect connected production processes provides greater value for operational planning. Digital Twins can represent these dependencies and enable organizations to investigate potential disruption scenarios before they occur. Consequently, the proposed approach moves industrial operations toward a proactive model in which real-time intelligence and virtual simulation contribute directly to operational decision-making.

Despite these benefits, the study establishes that successful deployment requires more than connecting sensors to AI models and creating virtual representations of industrial assets. Data quality, model reliability, cybersecurity, interoperability, synchronization, and human expertise are essential to achieving dependable results. Edge AI models must be continuously evaluated because changes in machine conditions, production configurations, environmental factors, or sensor characteristics can influence model performance. Similarly, Digital Twins must remain synchronized with their physical counterparts; otherwise, decisions based on inaccurate virtual representations may introduce

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additional operational risks. Cybersecurity must be embedded throughout the architecture because connected industrial infrastructure can expose critical assets to new threats. Strong authentication, authorization, encryption, secure software updates, network segmentation, and continuous anomaly monitoring are therefore essential components of a resilient architecture. Human operators also remain important because AI-generated alerts and recommendations should support rather than eliminate expert judgment, particularly when decisions affect safety-critical processes. The overall conclusion is that Edge AI and Digital Twin technology are most valuable when implemented as interconnected components of a broader cyber-physical operational ecosystem. Edge intelligence provides timely awareness, Digital Twins provide contextual and predictive capabilities, and centralized infrastructure provides large-scale analytics and coordination. When these capabilities are supported by robust governance and cybersecurity practices, connected industrial environments can become more adaptive, observable, and capable of recovering from disruptions. The proposed framework consequently provides a foundation for future industrial systems in which real-time intelligence, virtual modeling, and distributed computing work together to improve operational continuity, maintenance planning, resource utilization, and long-term resilience.

VI. FUTURE WORK

Future research should focus on developing adaptive and autonomous Edge AI–Digital Twin architectures capable of responding to changing industrial conditions. Current AI models can experience performance degradation when machinery is modified, production conditions change, or sensor characteristics evolve. Future systems can therefore incorporate continual learning, federated learning, transfer learning, and online model adaptation while maintaining appropriate safeguards against model drift and unreliable updates. Research should also investigate more sophisticated Digital Twins capable of representing interactions among machines, production lines, energy systems, logistics operations, and human activities. Combining real-time simulation with reinforcement learning could enable the system to evaluate alternative operational strategies and identify responses to potential disruptions before they affect physical production. Further research can examine hierarchical Digital Twin architectures in which asset-level twins interact with process-level and facility-level twins. Such architectures could provide increasingly comprehensive views of industrial dependencies and improve disruption analysis. Another research direction involves developing lightweight AI models specifically optimized for resource-constrained edge hardware, reducing computational and energy requirements while maintaining adequate accuracy.

Future work should additionally investigate security, interoperability, and large-scale deployment. Industrial environments contain equipment from different manufacturers and generations, making standardized communication and data models important for scalable implementation. Future studies can evaluate open industrial interoperability frameworks and investigate mechanisms for securely exchanging information among edge devices, Digital Twins, supervisory systems, and cloud platforms. Cybersecurity research should address adversarial attacks against edge AI models, manipulation of Digital Twin data, compromised sensors, unauthorized device access, and malicious model updates. Zero-trust security architectures and distributed monitoring mechanisms could provide stronger protection for increasingly interconnected industrial systems. Large-scale field experiments should also be conducted to evaluate the framework across different industries, including manufacturing, energy, transportation, and process industries. Evaluation should consider latency, prediction accuracy, downtime reduction, energy consumption, communication overhead, recovery time, cybersecurity incidents, and operational costs. Finally, future research should examine human-AI collaboration, determining how operators can effectively interpret AI-generated alerts and Digital Twin simulations while retaining appropriate control over critical decisions. These developments can transform the proposed framework into a continuously learning, secure, and resilient industrial intelligence platform capable of supporting increasingly autonomous connected operations.

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