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(Review Article)

Enterprise integration for manufacturing using IoT: A framework for real-time data exchange, predictive maintenance, and smart factory operations

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Abstract

Manufacturing enterprises increasingly rely on interconnected sensors, controllers, and software platforms that convert physical operations into continuous streams of actionable information. Enterprise integration for manufacturing links machine-level Internet of Things (IoT) devices with resource planning, execution, and quality systems, creating a unified environment where production data moves in real time across organizational boundaries. This convergence transforms isolated production lines into responsive, self-monitoring ecosystems capable of forecasting equipment failures before they occur and adjusting operations dynamically. Core outcomes include reduced unplanned downtime, extended equipment life, improved asset utilization, and tighter alignment between shop-floor execution and enterprise-level decision-making. Predictive maintenance emerges as a central capability within this framework, using sensor-derived condition data and machine learning models to anticipate failures and schedule interventions before costly breakdowns occur. Digital twins extend these capabilities further, offering virtual replicas of physical assets that mirror real-world behavior and support simulation, optimization, and remote diagnostics. Middleware platforms and standardized communication protocols such as MQTT and OPC UA enable interoperability between heterogeneous devices and enterprise resource planning, manufacturing execution, and supply chain management systems, addressing long-standing barriers of data silos and fragmented visibility. Practical significance extends beyond operational efficiency: organizations that integrate IoT with enterprise systems gain measurable improvements in energy consumption, resource allocation, and product quality, while building the foundation for adaptive, self-optimizing smart factories. Persistent barriers, including cybersecurity exposure, legacy-system compatibility, and the cost of large-scale sensor deployment, continue to shape adoption decisions across industries of varying scale. Manufacturers that align technical architecture with organizational processes convert raw sensor output into a strategic asset, positioning smart factory operations as a decisive factor in industrial competitiveness.

Keywords: Industrial Internet of Things; Enterprise integration; Predictive maintenance; Digital twin; Smart factory

1. Introduction

1.1. The Shift Toward Connected Manufacturing

The modern manufacturing enterprise no longer operates as a collection of isolated production cells. Machine tools, conveyors, and quality stations now generate continuous streams of condition data that, once confined to local control panels, are collected, transmitted, and interpreted across the entire organization. A layered Industrial Internet of Things data management system, organized around physical, network, middleware, database, and application layers, provides the structural backbone for this shift, allowing enterprises to manage large volumes of heterogeneous industrial data while supporting downstream services such as product lifecycle management, enterprise resource planning, supply chain management, manufacturing execution, quality management, and warehouse management [1]. Rather than

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treating each of these enterprise functions as a separate silo, this layered structure gives manufacturers a common data foundation from which multiple applications can draw simultaneously.

Building on this foundation, deep learning has extended what predictive maintenance can accomplish at the machine level. Long short-term memory autoencoder models applied to cyber-physical production systems can learn the normal operating signature of a machine directly from sensor time series and flag deviations that indicate a developing fault, often well before the anomaly would be noticeable through conventional threshold-based monitoring [2]. Rather than reacting to equipment failure after the fact, or servicing machines on a fixed calendar regardless of actual condition, manufacturers increasingly draw on this kind of live, learned pattern recognition to schedule interventions precisely when they are needed. These developments illustrate a broader pattern: enterprise integration for manufacturing is not a single technology but a composite capability built from layered data infrastructure, learned analytics, and organizational decision-making working together.

1.2. Scope and Structure of the Framework

The framework examined in this article addresses four interlocking concerns that recur across connected manufacturing environments: the architectural foundations that allow devices and enterprise applications to exchange data reliably; the reworking of enterprise architecture required to accommodate digital twins and machine learning; the practical mechanics of predictive maintenance and enterprise data management; and the operational patterns that characterize real-time smart factory analytics. Each of these concerns is treated in turn in the sections that follow, moving from architectural principles toward applied operational practice. The intent is to present a coherent, end-to-end view of how enterprise integration converts distributed sensor data into coordinated action, rather than treating connectivity, analytics, and enterprise systems as separate initiatives pursued independently.

Table 1 Categories of Technology Layers Supporting Enterprise Integration in Manufacturing

Technology Category	Representative Elements	Primary Function
Field devices	Sensors, actuators, programmable logic controllers	Capture and act on physical process conditions
Connectivity layer	Industrial Ethernet, wireless gateways, protocol adapters	Move data between the factory floor and higher-level systems
Middleware	Message brokers, standardized communication protocols	Ensure interoperability across heterogeneous devices
Analytics platforms	Machine learning pipelines, digital twin engines	Interpret data and forecast operational outcomes
Enterprise applications	Resource planning, execution, and quality systems	Translate insights into scheduling and business decisions

2. Architectural Foundations: Data, Intelligence, and Control in IoT-Enabled Manufacturing

2.1. Data Layers and Machine Learning Integration

Connected manufacturing environments generate data across a spectrum of forms, velocities, and structures, ranging from raw device readings to processed business records, and the volume of this data has outpaced what conventional relational systems were designed to handle. A dedicated analytics environment architecture for industrial cyber-physical systems addresses this gap by organizing big data ingestion, storage, and analysis into distinct functional tiers, allowing manufacturers to process high-frequency sensor streams alongside slower-moving business data without one workload degrading the other [3]. This kind of architecture treats analytics not as an add-on to existing infrastructure but as a first-class layer designed specifically for the volume and velocity that industrial cyber-physical systems produce. For manufacturing specifically, this means that anomaly detection, quality classification, and capacity forecasting can draw on a shared, purpose-built analytics substrate rather than competing for resources within general-purpose enterprise databases.

Layered on top of this data infrastructure is a predictive dimension concerned with how intelligent systems act on what they learn. A predictive maintenance model developed for flexible manufacturing under the Industry 4.0 paradigm illustrates this coupling directly: raw data generated by machine tools, factory processes, and information systems is collected and processed through a big data analytics platform, then used to support maintenance-related decision-making by factory operators in near real time [4]. This model treats predictive maintenance not as an isolated analytical exercise but as a service embedded within the broader collaborative industry context, where business processes and maintenance decisions are coordinated across factories and enterprises rather than confined to a single production line. This coupling is what allows a manufacturing enterprise to move from passive data collection toward active, coordinated operation.

2.2. From Architecture to Enterprise-Wide Integration

The convergence of purpose-built analytics architecture and model-driven predictive maintenance creates the conditions necessary for enterprise-wide integration, which is examined in detail in the following section. Establishing this architectural foundation first is important because digital twins and enterprise-scale analytics cannot function reliably without a dependable data and control substrate beneath them. Middleware, layered analytics environments, and coordinated predictive models therefore represent not peripheral infrastructure but the load-bearing architecture on which higher-level enterprise integration depends.

Table 2 Components of an IoT-Enabled Control Architecture

Architectural Component	Role Within the Manufacturing Environment
Data acquisition layer	Collects raw signals from sensors and connected equipment
Edge intelligence	Performs local filtering, anomaly detection, and pre-processing
Cyber-physical control	Links virtual models to physical actuation in real time
Machine learning services	Classifies patterns and generates predictive outputs
Human-machine interface	Presents insights to operators and supports override decisions

3. Enterprise Architecture Integration: Digital Twins and Intelligent Systems

3.1. Extending IoT Integration to Asset Verification and Inspection

Enterprise integration extends beyond production machinery into the inspection and verification processes that keep distributed assets accountable across an organization. Asset inspection has traditionally relied on manual, poorly digitized procedures that leave inspectors to record conditions on paper or in disconnected spreadsheets, creating gaps between what the shop floor observes and what enterprise systems record. Reworking these procedures around connected sensing combined with distributed ledger technology allows inspection records to be captured, verified, and shared in a way that is more efficient, reliable, and straightforward than legacy approaches, while giving multiple stakeholders, including original equipment manufacturers, owners, and inspectors, a consistent and tamper-resistant view of asset condition [5]. This pattern generalizes beyond its original mining-sector setting: any manufacturing enterprise that depends on distributed, difficult-to-access assets faces a similar need to convert inspection data into a trustworthy, shared enterprise record rather than a fragmented paper trail.

This enterprise-level positioning of asset data is what distinguishes current practice from earlier, narrower applications confined to a single inspection checklist or maintenance log. When inspection and condition data are connected not only to the physical asset but also to planning and scheduling systems, they become a shared reference point that different departments can consult, reducing the ambiguity that arises when maintenance, production planning, and quality teams rely on separate, inconsistent records of asset condition.

3.2. Reworking Enterprise Architecture for IoT Integration

Realizing this shared, enterprise-wide view requires more than deploying new software; it requires reworking how enterprise resources are digitally represented and transmitted throughout the organization. A mechanism for digital transmission of key enterprise aspects built around Internet of Things technology demonstrates that connecting resource-management functions directly to IoT data flows can meaningfully improve the efficiency of resource integration across the enterprise while reducing operating costs [6]. Rather than treating IoT connectivity and enterprise resource integration as separate initiatives, this approach embeds device-level data transmission directly into the mechanisms enterprises already use to manage their resources, aligning technical architecture with organizational processes rather than layering one on top of the other after the fact. The practical implication is that enterprise architecture itself becomes a living structure, continuously adjusted as new device types, data sources, and integration mechanisms are introduced into the manufacturing environment.

Table 3 Enterprise Systems Connected Through IoT-Enabled Asset and Resource Integration

Enterprise System	Integration Role
Enterprise resource planning (ERP)	Aligns inspection and resource-transmission data with procurement and financial planning
Manufacturing execution system (MES)	Coordinates production scheduling based on verified asset condition records
Supply chain management (SCM)	Uses inspection and resource data to adjust logistics and supplier coordination
Quality management system (QMS)	Cross-references digitized inspection records with observed quality parameters
Warehouse management system (WMS)	Synchronizes inventory decisions with verified asset and resource records

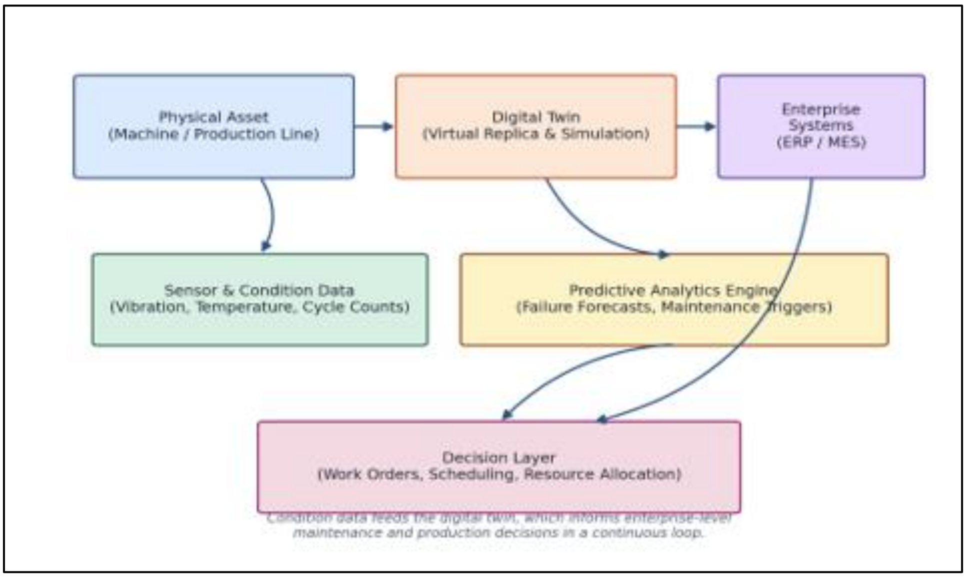

Figure 1 Digital twin data flow connecting physical assets, simulation, analytics, and enterprise decision-making.

4. Predictive Maintenance and Real-Time Data Management in Smart Factories

4.1. Persistent Challenges in AI- and IoT-Based Predictive Maintenance

Translating sensor output into operational value depends on disciplined data management practices at the enterprise level, and a comprehensive review of predictive maintenance implementations identifies where these practices most often break down. Data heterogeneity across device types and vendors, inconsistent sensor calibration, incomplete historical failure records, and the difficulty of generalizing models trained on one machine class to another all limit how reliably artificial intelligence and IoT-based predictive maintenance perform once deployed outside controlled pilot conditions [7]. These challenges generalize directly across industrial settings: performance data collected from machinery, once integrated into a coherent enterprise data platform with consistent governance and data models, becomes the foundation for reliable predictive maintenance, whereas fragmented or inconsistently governed data undermines even well-designed predictive algorithms. Building this foundation typically involves establishing consistent data models, governance rules, and storage architectures capable of handling the volume and variety generated by distributed sensor networks.

4.2. Machine Learning as the Analytical Engine Behind Predictive Maintenance

With a coherent data foundation in place, and its challenges understood, machine learning can be layered on top to forecast machine failures directly. Reviewing machine learning-enabled IoT from complementary data, application, and industry perspectives shows that the discipline's value in industrial settings comes from combining continuously sensed data with models capable of detecting patterns that would otherwise remain hidden within routine equipment readings, extending automated decision-making from centralized data centers out toward edge and fog computing closer to the machines themselves [8]. Predictive maintenance powered by such models enables analysis of incoming sensor data to estimate the probability of failure with meaningfully greater accuracy than fixed-interval servicing, allowing maintenance teams to take preemptive action rather than waiting for a fault to manifest. This capability directly links the enterprise data management practices described above with tangible shop-floor outcomes, closing the gap between raw sensor telemetry and maintenance scheduling decisions made by plant personnel.

Table 4 Stages of an AI-Powered Predictive Maintenance Cycle

Stage	Description
Data collection	Continuous acquisition of vibration, temperature, and operational signals
Data integration	Consolidation of sensor streams into enterprise data platforms
Condition assessment	Comparison of current readings against established baselines
Failure forecasting	Application of machine learning models to estimate failure likelihood
Maintenance scheduling	Generation of work orders aligned with predicted failure windows

5. Smart Factory Operations: Real-Time Analytics and Future Directions

5.1. Intelligent Control as the Bridge to Autonomous Operation

Smart factory operations depend on control architectures capable of merging sensed data with automated action with minimal delay. Intelligent control research situated within the Industry 4.0 paradigm frames this merging of physical and virtual representations of production assets as the defining feature of cyber-physical production systems, and identifies tightly coupled sensing, computation, and actuation, rather than separately managed subsystems, as the path toward the next iteration of industrial automation commonly described as Industry 5.0 [9]. Within a smart factory, this coupling functions as the bridge between the analytics and predictive maintenance capabilities developed earlier in this framework and the physical actuation that ultimately adjusts machine behavior. The modular nature of such control systems, in which sensing, computation, and actuation remain distinct but tightly coordinated stages, allows manufacturers to adapt the same underlying control philosophy to different equipment classes without redesigning the system from the ground up.

5.2. Digital Twins as the Operational Core of the Smart Factory

Applied within specific facility contexts, intelligent control and predictive analytics converge most visibly in the digital twin, which has become a critical component of the intelligent factory. Digital twin technology enables manufacturing companies to build better products, detect physical issues sooner, and predict outcomes more accurately, and its adoption has measurably reduced the cost of developing new manufacturing approaches, improved efficiency, reduced waste, and minimized batch-to-batch variability, particularly as manufacturers sought resilience following recent supply chain disruption [10]. Rather than functioning as an isolated simulation tool, the digital twin increasingly sits at the center of enterprise operations, extending into smart logistics and supply chain management alongside its original role in production monitoring. Taken together with the intelligent control foundations described above, these findings point toward smart factories that increasingly close the loop between sensing, prediction, and action with limited manual intervention, extending the enterprise integration framework introduced earlier in this article into fully operational practice.

Table 5 Categories of Smart Factory Operational Functions

Operational Function	Supporting Technology Category
Real-time monitoring	Distributed sensor networks and edge gateways
Coupled sensing and actuation	Cyber-physical control systems and intelligent controllers
Virtual simulation	Digital twin platforms mirroring physical assets
Automated alerting	Application programming interfaces and dashboards
Adaptive scheduling	Enterprise systems synchronized with twin and control outputs

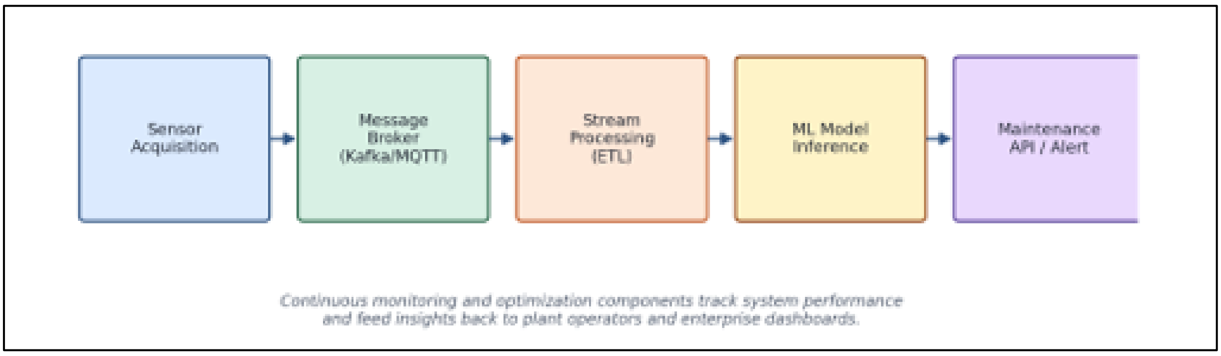

Figure 2 Real-time processing pipeline linking sensor acquisition, intelligent control, and alerting within smart factory operations.

Figure 3 Closed-loop feedback cycle linking sensing, analysis, prediction, decision-making, and action in smart factory operations

6. Conclusion

Enterprise integration for manufacturing draws together field-level sensing, middleware and communication standards, machine learning, digital twins, and enterprise applications into a single, continuously operating system. Layered architectures establish the technical substrate that allows condition data to move reliably from individual machines to organization-wide planning systems, while reworked enterprise architectures accommodate the machine learning and cloud technologies that this data ultimately requires. Digital twins extend this substrate into a shared representation of physical assets that different departments can consult simultaneously, replacing fragmented, department-specific views of equipment condition with a coherent enterprise-wide picture. Predictive maintenance stands out as the most immediately measurable outcome of this integration, converting continuously collected sensor data into scheduled interventions that reduce downtime and extend equipment life, while disciplined enterprise data management frameworks ensure that this data remains usable rather than merely abundant.

Smart factory operations built on real-time streaming architectures demonstrate that these gains extend beyond individual machines to entire facilities, with scalable pipelines supporting diverse equipment classes and operational contexts. The practical implication for manufacturing organizations is that connectivity investments deliver the greatest return when paired with corresponding investment in data governance, enterprise architecture redesign, and cross-departmental access to shared digital representations of physical assets. Manufacturers that treat sensing, analytics, and enterprise systems as a single integrated framework, rather than as separate initiatives pursued in isolation, are best positioned to convert continuous data flow into consistent operational advantage across production, maintenance, and supply chain functions.

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