Data Engineering and Applications

Review Paper

Harnessing Data Engineering for Intelligent Manufacturing: Digital Twin–Algorithm Fusion and Applications

Giorgos Papadopoulos[1, *], Sofia Dimitriou[2] and Despina Makris[2]

[1] Department of Digital Systems, University of Thessaly, Volos 38334, Greece
[2] Department of Information and Communication Systems Engineering, University of Crete, Heraklion 70013, Greece
*Corresponding author: papadopoulos@uot.edu.gr

Abstract. With the advancement of Industry 4.0, intelligent manufacturing has become an inevitable trend in the development of the manufacturing sector. The integration of digital twins and intelligent algorithms offers new avenues for optimizing smart manufacturing systems. This paper first elucidates the background and significance of this integration, analyzing its importance and potential value in optimizing smart manufacturing systems. It then explores the concepts and reference architectures of digital twins and smart manufacturing optimization, including conceptual evolution and reference architecture composition. It then elaborates on key technological systems such as data-driven modeling, multimodal perception, real-time synchronization, intelligent decision-making, distributed computing, and security detection. The paper examines the application of digital twin-intelligent algorithm integration in discrete production lines, process manufacturing, major equipment manufacturing, and collaborative robot clusters, analyzes current challenges and bottlenecks, and concludes with an outlook on future development trends.

Keywords: *Digital Twin, Intelligent Algorithms, Intelligent Manufacturing System, System Optimization, Convergence Applications*

Received on 30 September 2024, Accepted on 10 December 2024, Published on 28 December 2024

Introduction

Manufacturing serves as the backbone of the global economy, facing challenges from intensifying market competition and increasingly personalized consumer demands [1]. Traditional manufacturing urgently requires transformation and upgrading due to issues such as low production efficiency, resource waste, and unstable product quality [2]. Smart manufacturing has emerged as a key development trend, and the integration of digital twins with intelligent algorithms offers an innovative pathway for optimizing smart manufacturing systems [3]. Digital twins construct virtual models that mirror physical entities, while intelligent algorithms enhance system performance through data analysis and model optimization. Their integration enables real-time monitoring, simulation, prediction, and optimization of production processes, making it pivotal for the intelligent transformation of manufacturing [4].

The fusion of digital twins and intelligent algorithms holds significant importance in optimizing smart manufacturing systems [5]. In practical terms, this integration enhances production efficiency, reduces costs, improves product quality and corporate competitiveness, increases manufacturing system flexibility and adaptability, and enables enterprises to respond swiftly to market changes [6-8]. Regarding potential value, it will drive deeper development in intelligent manufacturing, catalyze new models such as smart factories and intelligent production, provide fresh perspectives for sustainable manufacturing development, promote collaborative optimization across industrial chains, and elevate overall industry efficiency and competitiveness [9].

In recent years, this field has garnered extensive attention from academia and industry, with related research steadily increasing [10]. Digital twin technology has made progress in virtual modeling and real-time mapping, while intelligent algorithms have found numerous applications in optimizing production scheduling and fault prediction [11-13]. Scholars and enterprises worldwide have actively explored its applications in automotive, aerospace, and electronics manufacturing, achieving notable results such as enhanced production efficiency and reduced equipment failure rates. However, challenges persist: prominent data quality and security issues, significant difficulties in integrating and processing multi-source heterogeneous data, room for improvement in real-time synchronization accuracy and efficiency, insufficient adaptability and scalability of intelligent algorithms, and poor technology integration and interoperability [14].

This paper focuses on optimizing intelligent manufacturing systems by constructing virtual models of manufacturing systems through digital twins and integrating intelligent algorithms for optimization decisions, thereby achieving intelligent management and optimization of production processes. Key contributions include: (1) Comprehensively reviewing the current state of research on integrating digital twins with intelligent algorithms for intelligent manufacturing system optimization, summarizing key technologies, application domains, and development trends to provide a systematic reference for future research; (2) It conducts an in-depth analysis of challenges and bottlenecks in this integration process, dissecting issues related to data, technology, and application to provide a basis for future research directions; (3) It demonstrates the application effectiveness and value through case studies, validating its efficacy and offering practical guidance for manufacturing enterprises to advance smart manufacturing development.

DT-Smart Manufacturing Optimization: Concepts and Reference Architecture

Concept Evolution

The concept of digital twins was first proposed by Michael Grieves in 2002. Initially applied primarily to product lifecycle management, it focused on simulating and optimizing stages such as product design, production, usage, and maintenance through virtual models. The core idea at the time was to create a virtual “information mirror” that digitally describes physical products to better understand and manage their lifecycle [15]. During this phase, digital twins primarily focused on integrating and visualizing product data. By establishing models of products in virtual spaces, they enabled centralized management and analysis of product information, providing a basis for design improvements and production planning [16].

However, with the rapid advancement of emerging technologies such as the Internet of Things (IoT) [17], big data [18], cloud computing [19], and artificial intelligence (AI) [20], the concept of digital twins has progressively expanded and enriched. Its functionalities and application scope have undergone a qualitative leap [21]. Driven by IoT technology, numerous sensors are deployed across physical equipment and production environments, enabling real-time collection of multidimensional information including operational status data, production process data, and environmental data [22]. This vast volume of data provides rich material for constructing and updating digital twin models, transforming them from static product representations into dynamic reflections of physical entities' real-time states.

Concurrently, big data technology provides robust data storage and analytical capabilities for digital twins. It enables efficient processing and deep mining of collected massive datasets to extract valuable insights and knowledge, establishing a data foundation for optimizing digital twin models and supporting decision-making [23]. Cloud computing technology provides the elastic infrastructure needed to scale computing and storage resources for digital twins, enabling digital twin systems to rapidly respond to various changes and demands during production processes, ensuring system real-time performance and efficiency [24]. Artificial intelligence technologies, particularly machine learning and deep learning algorithms, endow digital twins with intelligent decision-making capabilities. By training and analyzing digital twin models, functions such as predictive analytics for production processes, fault diagnosis and early warning, and production scheduling optimization can be achieved [25].

In the field of smart manufacturing, the application of digital twins is increasingly widespread, emerging as one of the key technologies for optimizing smart manufacturing systems [26]. It not only maps the real-time status of physical entities—such as equipment operating parameters, production progress, and quality conditions—but also integrates intelligent algorithms to simulate, predict, and optimize production processes [27].

The application of digital twins in smart manufacturing has evolved from initial equipment-level digital twins to production line-level digital twins, and further to workshop-level and even factory-level digital twins [28]. Equipment-level digital twins primarily focus on monitoring the operational status and diagnosing faults of individual machines. By collecting and analyzing real-time equipment data, they enable precise maintenance and management. Production line-level digital twins concentrate on simulating and optimizing the entire production process, encompassing aspects like production planning, scheduling optimization, and quality control [29]. Workshop-level and factory-level digital twins further extend the technology to broader production scenarios, enabling comprehensive monitoring, optimization, and decision support for the entire production system [30].

Table 1. presents a technical comparison of digital twins across different development stages.

Development Stage	Time Range	Core Technologies	Application Scenarios	Functional Features
Origin Stage	2002-2010	Product Modeling PLM Technology	Product Lifecycle Management	Static Model Data Integration and Visualization
IoT Integration Stage	2010-2015	IoT Sensor Technology	Equipment Status Monitoring Remote Monitoring	Real-Time Data Acquisition Dynamic Mapping
Big Data and Cloud Computing Stage	2015-2018	Big Data Cloud Computing	Production Data Analysis Cloud Digital Twin	Data Analysis and Mining Elastic Computing Resources
Artificial Intelligence and Intelligence Stage	2018-Present	Machine Learning Deep Learning Reinforcement Learning	Intelligent Decision Making Predictive Maintenance	Intelligent Decision Predictive Analysis Adaptive Optimization

Table 1 summarizes the evolution of digital twin technology over time, highlighting the key technological advancements and their corresponding application scenarios. Each development stage introduces new capabilities that progressively enhance the functionality and applicability of digital twins in intelligent manufacturing systems. Understanding these stages is crucial for researchers and practitioners to align their efforts with current trends and future possibilities.

To better illustrate the developmental trajectory and key technological milestones of digital twin technology, Figure 1 provides a comprehensive visualization of its evolution from the initial concept proposed in 2002 through to its current integration with advanced artificial intelligence techniques. This figure captures the pivotal stages in the transformation of digital twins—from static product lifecycle models to dynamic, intelligent manufacturing systems—highlighting how emerging technologies such as IoT, big data, cloud computing, and AI have progressively expanded both the scope and capabilities of digital twins. By examining this evolution, readers can gain deeper insight into the foundational technologies that underpin modern intelligent manufacturing optimization, setting the stage for understanding the subsequent architectural and functional advancements discussed throughout this paper.

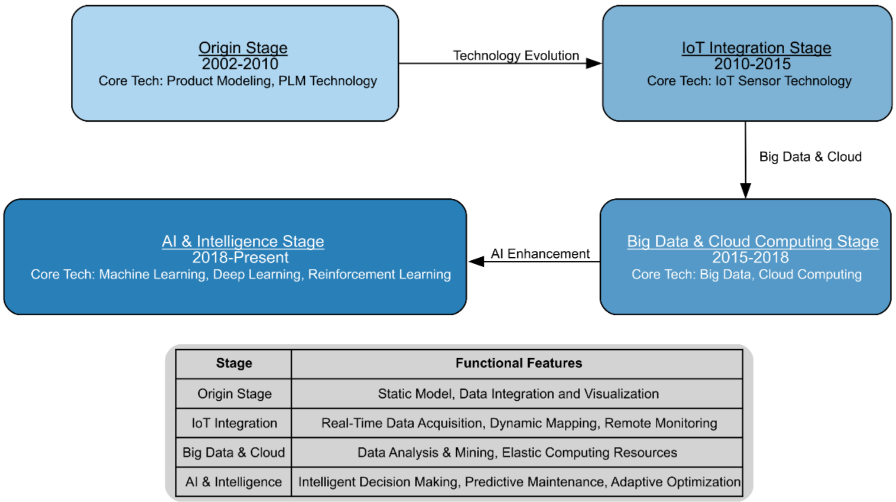

Figure 1. Evolution Stages and Core Technologies of Digital Twin

Figure 1 provides a comprehensive overview of the progressive development of digital twin technology, tracing its origins from initial product lifecycle management applications to the current integration with advanced technologies such as IoT, big data, cloud computing, and artificial intelligence. By highlighting the key technological milestones at each stage, the illustration aids readers in understanding how digital twin capabilities have expanded from static modeling to dynamic, intelligent systems that respond to real-time data. This visualization serves not only as a historical record but also as a foundational reference for researchers and practitioners seeking to align their work with established technological frameworks. Moreover, it emphasizes the critical role of emerging technologies in enhancing the fidelity, responsiveness, and applicability of digital twins within complex manufacturing environments.

Reference Architecture

Digital twin technology enables deep integration between the physical and information worlds, providing comprehensive support for optimizing intelligent manufacturing systems [31]. From data acquisition at the device layer, through data processing at the data layer, to model construction at the model layer, and finally to optimization decisions at the application layer, each level collaborates to form a complete digital twin-driven intelligent manufacturing system optimization framework [32]. The reference architecture for digital twins in intelligent manufacturing system optimization is illustrated in Table 2.

Table 2. Reference Architecture for Digital Twins in Intelligent Manufacturing System Optimization

No.	Reference Architecture Level	Specific Content
1	Device Layer	Sensors Controllers Robots Production Equipment etc.
2	Data Layer	Data Acquisition Module Data Cleaning Module Data Storage Module Data Management Module etc.
3	Model Layer	Geometric Modeling Tools Physical Modeling Tools Behavioral Modeling Tools Model Update and Management Tools etc.
4	Application Layer	Production Planning and Scheduling Module Quality Inspection and Control Module Equipment Failure Prediction and Maintenance Module Production Scheduling Optimization Module etc.

The reference architecture outlined above serves as a foundational blueprint for implementing digital twin systems in smart manufacturing environments. By delineating distinct layers—from physical devices to application modules—it facilitates a modular and scalable approach that can adapt to diverse manufacturing contexts. This layered structure supports efficient data flow, model updates, and decision-making processes essential for system optimization.

Understanding the complex interplay between physical manufacturing entities and their digital counterparts requires a clear conceptual framework. Figure 2 illustrates the reference architecture of digital twin systems specifically designed for intelligent manufacturing optimization. This layered architecture delineates the major components and functional modules, beginning with the device layer that encompasses sensors, controllers, and production equipment, progressing through the data layer responsible for acquisition and management, and culminating in the model and application layers where virtual modeling and decision-making occur. This hierarchical structure not only facilitates modular development and scalability but also ensures efficient data flow, synchronization, and system responsiveness. By visualizing this architecture, the figure serves as a critical blueprint for researchers and practitioners aiming to implement digital twin-driven optimization solutions tailored to the demands of modern manufacturing environments.

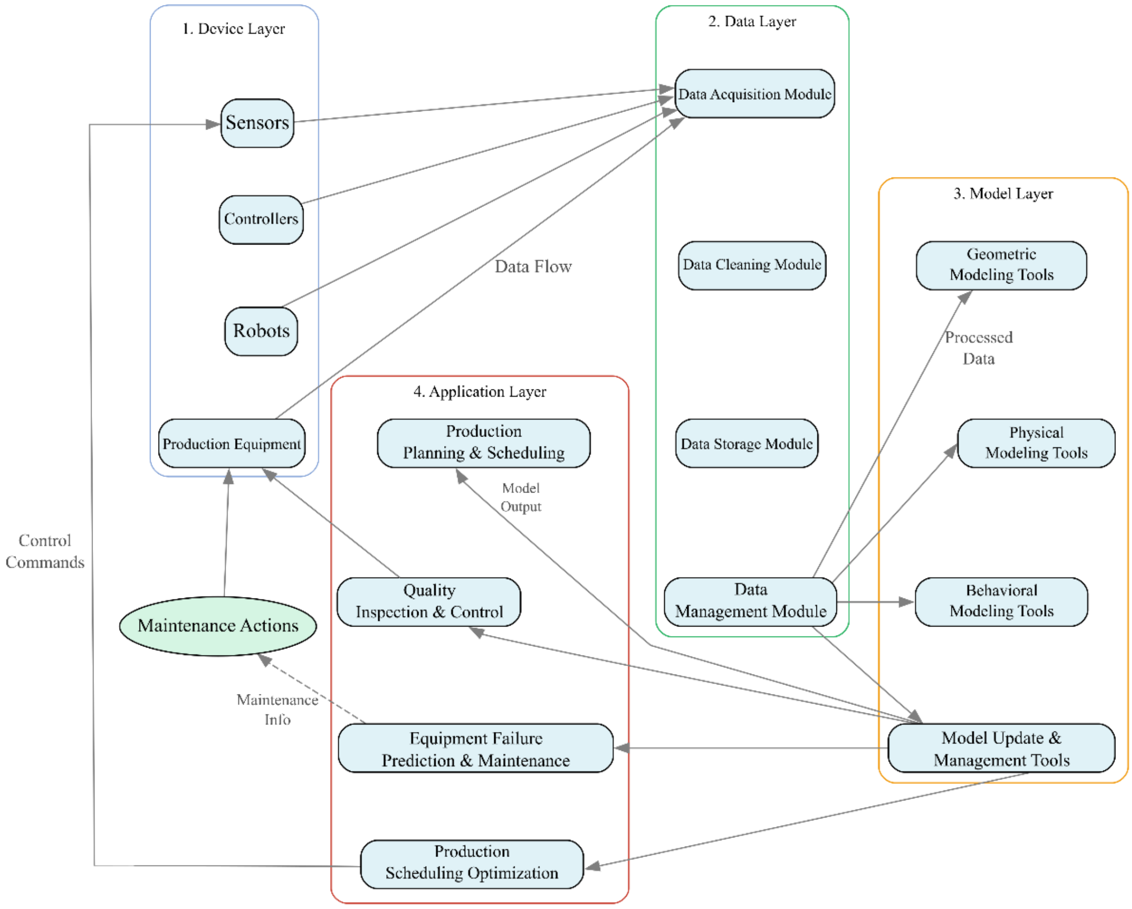

Figure 2. Reference Architecture of Digital Twin for Intelligent Manufacturing Optimization

The depicted reference architecture clearly delineates the layered structure essential for implementing digital twin systems in intelligent manufacturing contexts. Each layer—from the physical device layer responsible for real-time data acquisition, through the data management layer handling cleaning and storage, to the modeling layer where virtual representations are constructed and updated, and finally the application layer that supports decision-making and control—collaborates seamlessly to ensure system coherence. This modular design facilitates not only scalability and adaptability across diverse manufacturing scenarios but also enables efficient data transfer and synchronization between the physical and digital realms. The architecture underscores the importance of well-defined interfaces and robust data pipelines in maintaining the accuracy and timeliness of digital twin models, which are critical for achieving high-performance manufacturing optimization.

Key Technology Framework

Data-Driven Modeling

Data-driven modeling is one of the core technologies for digital twin systems. By leveraging machine learning, deep learning, and other algorithms to analyze and mine vast amounts of production data, it constructs models that accurately describe production processes and equipment behavior [33]. These models enhance our understanding and prediction of production system operational states, thereby enabling process optimization and decision support.

The core of data-driven modeling lies in extracting valuable information and knowledge from massive production data. In smart manufacturing environments, production data typically exhibits diversity, complexity, and dynamic characteristics [34]. Data-driven modeling techniques effectively process this data and transform it into models with practical significance. The data-driven modeling process generally includes steps such as data collection, data preprocessing, model selection and training, model validation and optimization [35].

During the model selection and training phase, appropriate machine learning or deep learning algorithms—such as linear regression [36], decision trees [37], support vector machines [38], and neural networks [39]-are chosen based on specific application scenarios and data characteristics. These models are then trained using preprocessed data [40]. The objective of training is to minimize the loss function, which quantifies the difference between predicted and actual values. This can be formally expressed as:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell\big(y_i, f(x_i;\theta)\big) \qquad (1)$$

In data-driven modeling, the primary goal during model training is to build a mathematical model that accurately predicts or describes the manufacturing process by analyzing extensive historical production data. The loss function $L(\theta)$ quantifies the discrepancy between the model's predictions and the true data, serving as a crucial criterion for model optimization.

Here, N denotes the total number of training samples, x_i is the input feature vector of the i-th sample, and y_i is its corresponding true output. The predictive model $f(x_i;\theta)$, parameterized by θ, outputs the predicted value for input x_i. The function $l(\cdot)$ measures the loss for each sample-common choices include mean squared error (MSE) for regression or cross-entropy for classification.

Minimizing the average loss over all samples allows the model to iteratively adjust parameters θ , improving its predictive accuracy. This process is fundamental in digital twin systems, where precise modeling of equipment behavior and production states is essential for reliable forecasting and process optimization.

Data-driven modeling stands as a cornerstone technology enabling digital twin systems to accurately represent and predict the behavior of manufacturing processes and equipment. Figure 3 outlines the comprehensive process flow involved in data-driven modeling, beginning with raw data collection from various production sources, followed by data preprocessing to ensure quality and consistency. The figure further depicts the critical phases of model selection and training, where appropriate machine learning or deep learning algorithms are applied to capture complex production dynamics. Finally, it shows the validation and optimization stages that refine model performance to meet operational requirements. By presenting this detailed workflow, the figure helps to clarify how data-driven approaches transform vast, heterogeneous manufacturing data into actionable models that support real-time monitoring, fault diagnosis, and process optimization in intelligent manufacturing systems.

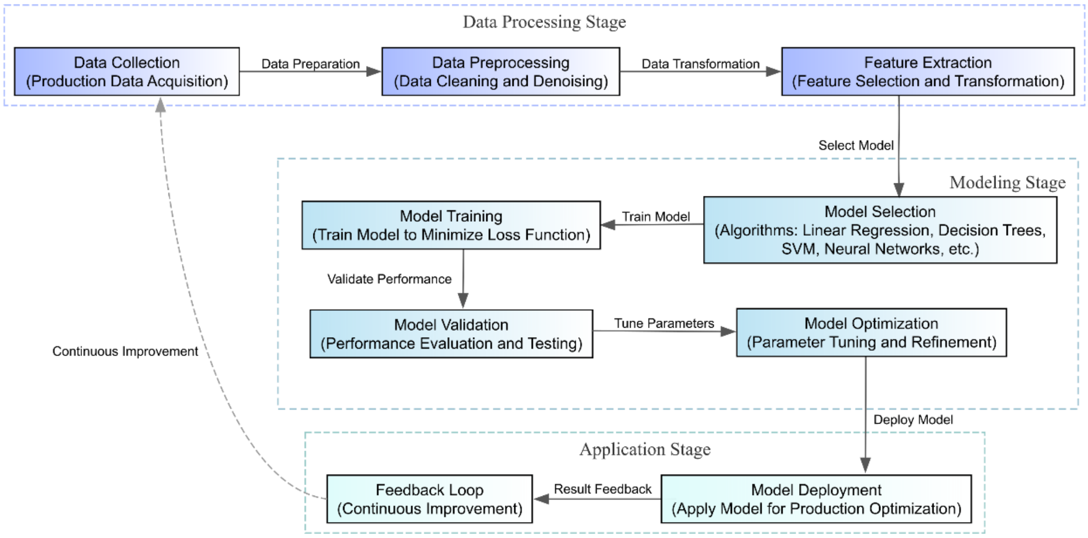

Figure 3. Data-Driven Modeling Process Flow

This flowchart offers a detailed depiction of the data-driven modeling workflow within digital twin systems, illustrating the transformation of raw production data into actionable predictive models. The process begins with comprehensive data collection, followed by rigorous preprocessing to cleanse and normalize inputs, ensuring the removal of noise and inconsistencies. Subsequent phases involve the selection and training of suitable machine learning and deep learning algorithms tailored to specific manufacturing challenges, enabling the capture of complex nonlinear relationships inherent in production processes. Model validation and continual optimization steps are critical to verify accuracy and improve robustness, ensuring that the resulting models reliably support real-time monitoring, fault detection, and process improvement. This structured approach highlights the interplay between data quality, algorithmic rigor, and domain knowledge in constructing effective digital twin models.

The characteristics of models based on various algorithms are summarized in Table 3. Reference [41] employs a random forest classification model trained on historical failure and normal operation data to predict the probability of equipment failure within a future timeframe.

Table 3. Application Scenarios for Different Types of Data-Driven Modeling Algorithms

Algorithm Type	Applicable Scenario	Advantages	Disadvantages
Linear Regression	Energy Consumption Prediction	Simple Model Easy to Understand and Interpret	Limited Capability for Nonlinear Relationships
Decision Tree	Equipment Fault Classification	Strong Visualization Easy to Interpret	Susceptible to Noise Prone to Overfitting
Support Vector Machine	Quality Inspection	Good Generalization Suitable for High-Dimensional Data	High Computational Complexity Sensitive to Parameter Selection
Neural Network	Image Recognition Natural Language Processing	Strong Modeling Capability Handles Complex Nonlinear Relationships	Easily Trapped in Local Optima

The reference architecture outlined above serves as a foundational blueprint for implementing digital twin systems in smart manufacturing environments. By delineating distinct layers—from physical devices to application modules—it facilitates a modular and scalable approach that can adapt to diverse manufacturing contexts. This layered structure supports efficient data flow, model updates, and decision-making processes essential for system optimization.

Data-driven modeling has multiple applications in smart manufacturing [42]. This enables early detection of potential equipment failures, allowing timely maintenance to reduce downtime and production losses. Additionally, data-driven modeling can optimize production processes by predicting metrics such as energy consumption and raw material utilization during production, providing decision support for production planning and scheduling.

Multimodal Perception

Multimodal perception is a critical technology enabling comprehensive, multidimensional sensing of physical entities within digital twin systems [43]. It integrates diverse sensor data—including visual, auditory, temperature, and pressure inputs—to provide richer, more holistic information support for digital twin models.

In smart manufacturing, applying multimodal perception technology significantly enhances the precision and accuracy of production site perception [44]. By integrating these diverse sensor data types, comprehensive perception of physical entities is achieved, providing more precise data support for updating and optimizing digital twin models. Applications of multimodal perception technology in smart manufacturing are shown in Table 4. Implementing multimodal perception involves multiple stages, including sensor data acquisition, preprocessing, feature extraction, and fusion [45].

Table 4. Research Directions in Medical Image Diagnosis

Perception Method	Application Scenario	Advantages
Visual Perception	Product Quality Inspection Material Identification and Positioning	Rich Information Can Obtain Shape Color Size etc.
Auditory Perception	Equipment Fault Diagnosis Production Environment Monitoring	Low Cost Remote Monitoring
Temperature Perception	Equipment Operation Status Monitoring Process Control	Strong Real-Time Nature Can Reflect Heat-Related States
Pressure Perception	Material Pressure Monitoring Equipment Operation Force Control	High Precision Direct Measurement of Force-Related Parameters

The diverse perception methods listed here demonstrate the importance of integrating multiple sensor modalities to capture comprehensive information about manufacturing processes. Each perception type contributes unique insights, and their fusion enhances the accuracy and reliability of digital twin models. This multimodal approach is increasingly vital for addressing complex industrial scenarios where single-sensor data may be insufficient.

Data fusion is the core component of multimodal perception. By employing suitable data fusion algorithms— such as Kalman filtering [46], Bayesian fusion [47],and deep learning fusion[48]- data from different sensors are integrated to generate a comprehensive， holistic perception outcome. The fusion process can be mathematically represented as：

$$S_{\text{fused}} = \sum_{j=1}^{M} w_j S_j, \sum_{j=1}^{M} w_j = 1, w_j \geq 0 \qquad (2)$$

Multimodal perception integrates heterogeneous sensor data to achieve more comprehensive and accurate sensing of physical entities. In this equation, S_j represents the data from the j-th sensor modality, such as visual images, temperature readings, or pressure signals. The corresponding weight w_j reflects the relative importance of each sensor's data in the fusion process.

The weights are non-negative and normalized such that their sum equals one, ensuring that the fused output S_{fused} is a convex combination of all sensor inputs. This weighted fusion enhances robustness by compensating for shortcomings or noise in individual sensors, yielding a richer and more reliable perception result. In intelligent manufacturing, such data fusion supports real-time updates of digital twin models, enabling accurate monitoring and predictive maintenance through comprehensive situational awareness.

The integration of multimodal perception technologies is essential for achieving comprehensive and accurate sensing in digital twin-enabled manufacturing systems. Figure 4 visually represents the framework for multimodal perception and data fusion, demonstrating how diverse sensor modalities—such as visual imaging, auditory signals, temperature measurements, and pressure sensing—are collected, preprocessed, and fused to provide a holistic understanding of the physical environment. This multimodal fusion enhances the robustness and precision of digital twin models by compensating for the limitations of individual sensors and capturing complex, multidimensional manufacturing phenomena. The figure highlights the importance of advanced data fusion algorithms in synthesizing heterogeneous data streams into a coherent perception output, thereby enabling more effective real-time monitoring, predictive maintenance, and intelligent decision-making within smart manufacturing ecosystems.

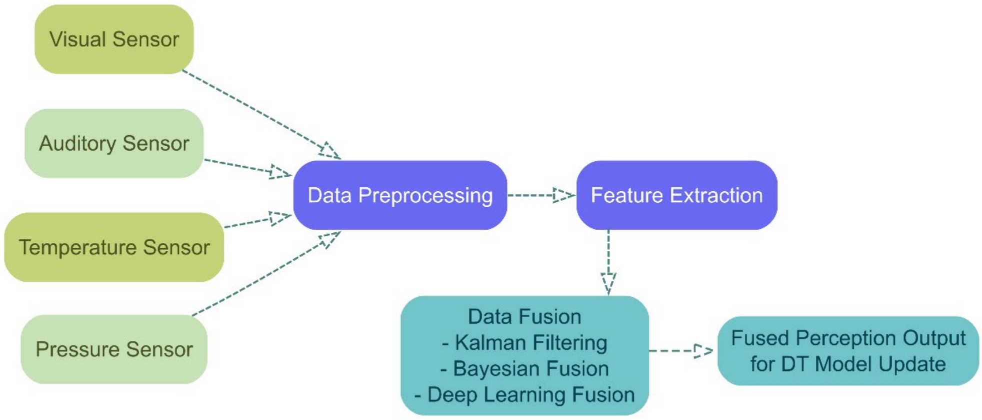

Figure 4. Multimodal Perception and Data Fusion Framework

The framework illustrated here emphasizes the integration of multiple sensory modalities to achieve a comprehensive and nuanced perception of manufacturing environments. By combining data streams from visual, auditory, temperature, and pressure sensors, the system overcomes the limitations associated with relying on a single sensor type, thereby enhancing the overall accuracy and reliability of digital twin models. The data fusion stage employs advanced algorithms to merge heterogeneous data sources into a coherent and unified representation, which is essential for capturing the multifaceted nature of physical processes on the production floor. This multimodal approach not only improves fault tolerance by compensating for sensor failures or anomalies but also enriches the data context available for predictive maintenance, operational control, and quality assurance. The framework thus forms a critical backbone for the real-time situational awareness required in intelligent manufacturing.

The advantage of multimodal perception lies in its ability to provide richer information than a single sensor, thereby enhancing the precision and accuracy of perceiving physical entities [49]. In industrial robot operations, [50] demonstrates that integrating data from visual and force sensors enables precise perception of object position and orientation, along with real-time control of operational forces, thereby enhancing robotic accuracy and safety. Furthermore, multimodal perception improves system robustness and reliability; when a sensor fails or data is lost, information from other sensors can compensate, ensuring uninterrupted system operation [51].

Real-Time Synchronization

Real-time synchronization technology is crucial for ensuring digital twin systems accurately reflect the real-time status of physical entities. It achieves real-time data interaction and synchronous updates between physical entities and digital twin models through efficient communication technologies and data transmission protocols [52].

In smart manufacturing environments, the dynamic and complex nature of production processes demands that digital twin systems acquire real-time status information from physical entities and promptly update the digital twin model [53]. On automated production lines, information such as equipment operational status, production progress, and material flow must be transmitted in real time to the digital twin system, enabling the digital twin model to accurately reflect current production conditions [54]. Simultaneously, decision outcomes and control commands from the digital twin system must be promptly fed back to physical entities to enable real-time optimization and control of production processes [55]. Application scenarios of real-time synchronization technology in smart manufacturing are analyzed in Table 5. Implementing real-time synchronization involves multiple stages including data acquisition, transmission, processing, and model updates [56].

Table 5. Applications of Real-Time Synchronization Technology in Smart Manufacturing

Application Scenario	Communication Technology	Data Transmission Protocol	Real-Time Requirement	Advantages
Automated Production Line Monitoring	Industrial Ethernet	OPC UA	Millisecond Level	Fast Transmission High Reliability
Industrial Robot Control	Profibus	Modbus TCP	Millisecond Level	Strong Real-Time Good Compatibility
Remote Equipment Monitoring	4G 5G	MQTT	Second Level	High Flexibility in Wireless Transmission

Real-time synchronization is a critical enabler for maintaining the coherence between physical systems and their digital counterparts. The communication technologies and protocols summarized in the table reflect the trade-offs between latency, reliability, and flexibility. Optimal selection and configuration of these technologies are key to ensuring timely and accurate digital twin updates in dynamic manufacturing environments.

The key to real-time synchronization technology lies in ensuring the timeliness and reliability of data transmission [57]. In practical applications, appropriate communication technologies and data transmission protocols must be selected based on specific production scenarios and requirements. Concurrently, measures such as data redundancy, error detection, and correction must be implemented to enhance transmission reliability and prevent data loss or errors that could lead to untimely or inaccurate updates of digital twin models [58]. The total data transmission delay D in real—time synchronization systems can be decomposed as：

$$D = D_{\text{propagation}} + D_{\text{transmission}} + D_{\text{processing}} + D_{\text{queueing}} \tag{3}$$

Real-time synchronization technology is fundamental to ensuring that digital twin systems accurately mirror the current status of physical entities by facilitating timely data exchange. The total delay D involved in this process is composed of several key components. The propagation delay, $D_{\text{propagation,}}$ refers to the time it takes for a signal to travel through the physical communication medium, which depends on the distance between devices and the speed of signal transmission. Following this is the transmission delay, $D_{\text{transmission,}}$ which represents the duration required to push the entire data packet onto the communication channel; this delay is influenced by the size of the data and the bandwidth of the network. Once the data is in the network, processing delay, $D_{\text{processing,}}$ arises due to the time taken by network devices to interpret packet headers, perform routing decisions, and conduct error checking. Additionally, queuing delay, $D_{\text{queueing,}}$ occurs when data packets wait in buffers, especially during periods of high network congestion. In the context of intelligent manufacturing, minimizing this overall delay is critical because excessive latency can cause the digital twin model to lag behind the physical system's true state, undermining the effectiveness of real-time monitoring, prediction, and control. Therefore, understanding and optimizing each component of the total delay is essential for designing efficient communication architectures that meet the stringent real-time requirements of modern smart manufacturing environments.

Intelligent Decision-Making

Intelligent decision-making technology serves as the core component for optimizing smart manufacturing systems within digital twin frameworks [59]. Based on digital twin models and data analysis results, it employs intelligent algorithms such as genetic algorithms [60], particle swarm optimization [61], and deep reinforcement learning [62] to make decisions regarding production planning, scheduling, and optimization. This enables the rapid generation of optimal decision schemes based on real-time production conditions, thereby improving production efficiency and resource utilization. A performance comparison of intelligent decision-making algorithms is shown in Table 6.

Table 6. Performance Comparison of Intelligent Decision-Making Algorithms

Algorithm Name	Applicable Problem	Advantages	Disadvantages
Genetic Algorithm	Combinatorial Optimization	Strong Global Search Ability	High Computation Large Parameter

	Problem such as Production Scheduling	Suitable for Complex Optimization Problems	Sensitivity Slow Convergence
Particle Swarm Optimization Algorithm	Continuous Optimization Problem such as Parameter Optimization	Fast Convergence Easy Implementation	Easily Trapped in Local Optima High Parameter Adjustment Requirements
Deep Reinforcement Learning	Interactive Decision Scenarios such as Robot Control	Can Learn Optimal Policies Adapt to Dynamic Environment Changes	Requires Large Amount of Training Data Long Training Time Poor Model Interpretability

The performance characteristics of various intelligent decision-making algorithms presented here highlight the diversity of approaches available for production optimization. Each algorithm offers distinct advantages suited to different problem types, while also presenting challenges such as computational complexity or susceptibility to local optima. Careful evaluation of these factors is necessary to implement effective decision-making modules within digital twin frameworks.

In intelligent manufacturing environments, production processes are complex and dynamic, involving multiple stages and extensive resource scheduling [63]. Traditional decision-making methods often struggle to meet real-time and accuracy requirements, whereas intelligent decision-making technologies can fully leverage the rich information and powerful data analysis capabilities provided by digital twin models to achieve intelligent optimization and decision support for production processes [60]. The implementation of intelligent decision-making technology typically involves steps such as objective definition, constraint setting, algorithm selection and optimization, and decision scheme generation and evaluation [63]. Genetic algorithms evaluate candidate solutions based on a fitness function that guides the search for optimal or near－optimal solutions． The fitness function F can be generally equationted as：

$$F = \max\{f(x) \mid x \in \mathcal{X}\} \qquad (4)$$

Distributed computing architectures address the computational demands of processing vast manufacturing data and complex digital twin models by distributing workloads across multiple computing nodes. The goal of load balancing is to evenly distribute tasks to avoid bottlenecks and maximize resource utilization.

In this equation, L_i denotes the computational load on node i, and $\bar{L} = \frac{1}{N}\sum_{i=1}^{N} L_i$ is the average load across all N nodes. Minimizing the variance σ^2 of node loads ensures that no individual node is significantly overburdened or underutilized. Achieving this balance improves the system's parallel efficiency, reduces latency in processing large-scale data, and ensures the real-time responsiveness of digital twin-enabled intelligent manufacturing systems.

Intelligent decision-making technology finds extensive applications in smart manufacturing. In production planning and scheduling, analyzing production data within digital twin models enables the use of intelligent algorithms to optimize production plans, rationally allocate production tasks and resources, reduce production waiting times and equipment idle time, and enhance production efficiency [64]. In quality control, real-time monitoring and analysis of production quality data based on digital twin models, combined with intelligent decision-making algorithms, enables timely detection of quality issues and implementation of corrective actions, thereby enhancing product quality stability and consistency [65]. For equipment maintenance, integrating operational data with fault prediction models allows intelligent decision-making to optimal maintenance schedules, balancing maintenance costs and equipment reliability to extend service life [66].

Distributed Computing

Distributed computing architecture addresses the massive production data processing and complex model computation demands in smart manufacturing systems [67]. It distributes computational tasks across multiple nodes for parallel processing, thereby enhancing system efficiency and response speed while ensuring the real-time performance and reliability of digital twin systems.

In smart manufacturing environments, production data volumes experience explosive growth as production scales expand and process complexity increases [68]. Traditional centralized computing architectures often struggle to meet the demands of large-scale data processing and complex model computations, frequently encountering computational bottlenecks and performance limitations that slow system responsiveness or even cause operational failures. Distributed computing technology effectively addresses this challenge by distributing computational tasks across multiple nodes. This approach fully leverages the computational resources of each node, enabling parallel processing and distributed storage. Distributed computing architectures strive to balance computational loads across multiple nodes to maximize efficiency and minimize bottlenecks. The load balancing objective can be mathematically expressed as minimizing the variance of node loads：

$$\min \sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (L_i - \bar{L})^2 \qquad (5)$$

In intelligent decision-making, especially when employing genetic algorithms and other evolutionary methods, the fitness function F evaluates the quality of candidate solutions x within the feasible solution space $\mathcal{X}$. The function $f(x)$ quantitatively measures each solution's performance with respect to the optimization objectives, such as minimizing production time, cost, or maximizing throughput.

The algorithm aims to find the solution x that maximizes the fitness value $f(x)$, representing the best or near-best decision under given constraints. Through iterative selection, crossover, and mutation, the population evolves toward increasingly optimal production schedules or resource allocations. This fitness-driven optimization is key to enabling digital twin systems to generate efficient, adaptive, and robust production plans that respond dynamically to real-time manufacturing conditions.

The distributed computing architecture primarily comprises components such as distributed file systems, distributed databases, and distributed computing frameworks. Distributed file systems store massive datasets, providing highly reliable and scalable data storage services [67]. Distributed databases manage structured and unstructured data, supporting high-concurrency read/write operations and rapid queries [68]. Distributed computing frameworks deliver parallel processing capabilities for efficient large-scale data processing and analysis [69]. Specific comparisons are detailed in Table 7.

Table 7. Comparison of Distributed Computing Frameworks

Computing Framework	Applicable Scenario	Advantages	Disadvantages
Hadoop	Large-Scale Data Batch Processing	Mature and Stable Good Community Support	High Latency Not Suitable for Real-Time Computing
Spark	Scenarios Requiring Fast Iterative Computing such as Machine Learning	In-Memory Computing Fast Speed Supports Real-Time Computing	Low Efficiency for Small File Processing Complex Resource Management
Storm	Real-Time Stream Data Processing	Low Latency High Real-Time	Low Fault Tolerance Needs to Cooperate with Distributed Storage Systems

Distributed computing frameworks play an indispensable role in handling the large-scale data and computational demands of intelligent manufacturing systems. The comparison above illustrates the suitability of each framework for different processing needs, ranging from batch to real-time stream processing. Selecting the appropriate framework ensures that digital twin systems can operate efficiently at scale and meet real-time performance requirements.

Security Monitoring

Security monitoring technology serves as a critical means to ensure the safe and stable operation of intelligent manufacturing systems. By establishing robust security monitoring mechanisms, it provides real-time surveillance and protection for cybersecurity, data security, and equipment security during production processes, thereby guaranteeing the normal functioning of intelligent manufacturing systems [60].

In the context of digital twin-enabled intelligent manufacturing, the complexity and interconnectedness of production systems significantly increase the potential attack surface. As manufacturing operations become more reliant on real-time data exchange, cloud platforms, and remote device management, vulnerabilities in network protocols, software, and endpoint devices can be exploited by malicious actors. Moreover, the integration of legacy equipment with modern digital infrastructure often results in inconsistent security standards and gaps in protection. Insider threats, whether unintentional due to human error or intentional acts of sabotage, also pose considerable risks to system integrity. Consequently, security monitoring technology must not only detect and respond to external cyber threats but also identify abnormal behaviors and potential failures originating from within the organization. Implementing multi-layered defense strategies—including continuous network traffic analysis, anomaly detection using artificial intelligence, and strict access control—has become essential. Furthermore, proactive measures such as regular vulnerability assessments, security patch management, and employee cybersecurity training are indispensable for maintaining a resilient manufacturing environment. As digital twins increasingly orchestrate and optimize core production activities, ensuring their security is foundational to safeguarding intellectual property, operational continuity, and the reputation of manufacturing enterprises.

In smart manufacturing environments, cybersecurity threats are escalating with the proliferation of industrial internet and the deep integration of cyber-physical systems. Cyberattacks can lead to severe consequences such as production system paralysis, data leakage or tampering, and equipment damage, causing substantial economic losses and societal impacts for enterprises. Therefore, the application of security detection technology in digital twin systems is particularly critical [70]. The application of security detection technologies in intelligent manufacturing systems primarily encompasses cybersecurity detection, data security detection, and equipment security detection. A detailed comparative analysis is presented in Table 8.

Table 8. Application of Security Detection Technologies in Intelligent Manufacturing Systems

Security Detection Aspect	Technical Means	Advantages	Disadvantages
Network Security Detection	Intrusion Detection System Firewall	Real-Time Monitoring and Prevention of Network Attacks	Limited Capability to Detect New Attacks Possible High False Alarm Rate
Data Security Detection	Data Encryption Access Control	Ensures Data Confidentiality and Integrity	Encryption and Decryption May Increase System Burden Affect Performance
Equipment Security Detection	Equipment Status Monitoring Fault Diagnosis	Improves Equipment Reliability and Security	High Sensor Cost Complex Data Processing

Security monitoring technologies are vital for safeguarding intelligent manufacturing systems against a range of threats. The table details various detection mechanisms, each with its own strengths and weaknesses. Integrating multiple security layers is often necessary to provide comprehensive protection, ensuring the integrity, confidentiality, and availability of manufacturing data and assets.

Application Domain Analysis

The application domains where digital twins and intelligent algorithms are integrated to address optimization challenges in smart manufacturing systems primarily encompass discrete production lines, process manufacturing, major equipment manufacturing, and collaborative robot clusters. Case comparisons are presented in Table 9.

Table 9. Case Comparisons Across Application Domains

Application Domain	Case	Application Effect
Discrete Production Line	Automobile Manufacturing Enterprises Optimize Production Planning and Scheduling through Digital Twins and Intelligent Algorithms	Production Efficiency Increased by 20 Percent Production Cost Reduced by 15 Percent
Process Manufacturing	Chemical Enterprises Use Digital Twins for Real-Time Monitoring and Optimization of Production Processes	Energy Utilization Rate Increased by 10 Percent Product Quality Stability Improved
Cluster Robot Collaboration	Multiple Robots Collaborate in Logistics Warehouses	Operational Efficiency Increased by 30 Percent Space Utilization Rate Improved

The case comparisons highlight how integrating digital twins with intelligent algorithms can yield measurable improvements across diverse manufacturing sectors. These real-world applications provide valuable insights into the practical benefits and challenges of deploying such technologies. They also serve as benchmarks for future developments aiming to further enhance manufacturing efficiency and flexibility.

In discrete manufacturing enterprises such as automotive and electronics industries, the integration of digital twins with intelligent algorithms can be applied to production planning and scheduling, production line balancing optimization, equipment failure prediction and maintenance [71]. By virtually modeling and simulating production processes for optimization, production efficiency is enhanced while costs are reduced. In process manufacturing industries like chemicals and pharmaceuticals, it can be applied to real-time production monitoring and optimization, quality prediction and control, and energy management [72]. Leveraging real-time data from digital twins and intelligent algorithm optimization enables refined production management and efficient resource utilization.

For manufacturing large, complex equipment in sectors such as aerospace and shipbuilding, it can be used for product design and validation, manufacturing process optimization, and equipment performance prediction and evaluation [73]. Digital twin technology provides a virtual testing and validation environment, reducing physical experimentation costs and risks while enhancing equipment R&D efficiency and quality. In multi-robot collaborative scenarios, such as logistics handling, digital twins facilitate real-time coordination and decision-making among robots. By integrating real-time data from multiple robots and intelligent algorithms, they enable precise movement planning, collision avoidance, and task allocation [74]. This technology optimizes resource allocation and improves operational efficiency. [73]. Digital twin technology provides a virtual testing and validation environment, reducing physical experimentation costs and risks while enhancing equipment R&D efficiency and quality.

Challenges and Bottlenecks

Although integrating digital twins with intelligent algorithms has achieved certain successes in optimizing smart manufacturing systems, the following challenges and bottlenecks persist: 1) The massive volume and diverse types of data generated in smart manufacturing systems make it difficult to ensure data accuracy, completeness, and consistency, impacting the construction and application of digital twin models [75]. 2) As production systems continuously evolve, models require real-time updates to maintain accuracy, imposing stringent demands on scalability and maintainability. 3) In high-real-time-demand scenarios such as robot control and production scheduling, digital twin systems must meet real-time requirements for data processing and computational efficiency [76]. Existing computational resources and technological capabilities struggle to fully satisfy the real-time demands of digital twins in large-scale intelligent manufacturing systems. 4) Digital twin technology involves vast amounts of production data and equipment information. Any leakage could inflict substantial losses on enterprises. Ensuring data security and privacy while preventing tampering or theft represents another critical challenge in integrating digital twins with intelligent algorithms [77].

In addition to the aforementioned challenges, another significant bottleneck lies in the integration of heterogeneous systems and standards within intelligent manufacturing environments. The manufacturing ecosystem traditionally encompasses a variety of legacy equipment, disparate data formats, and multiple communication protocols, all of which complicate the seamless integration necessary for effective digital twin deployment. Achieving true interoperability among such heterogeneous platforms has long been a critical technical hurdle. Additionally, the rapid evolution of industrial technologies up to recent years has already imposed continuous requirements for updating and maintaining digital twin models and intelligent algorithms, raising concerns about the sustainability and long-term maintenance costs of these systems. The human factor is also pivotal; the persistent shortage of skilled personnel with the expertise to operate, interpret, and optimize these advanced digital systems further impedes their widespread adoption. Overcoming these multifaceted challenges demands a comprehensive approach—one that emphasizes technical innovation, industry-wide standardization, and systematic workforce development—so as to fully realize the potential of digital twin-integrated intelligent manufacturing systems.

Conclusion

The integration of digital twins and intelligent algorithms provides robust technical support and innovative approaches for optimizing smart manufacturing systems. Through an in-depth exploration of the concept, reference architecture, key technological frameworks, application domains, and challenges of digital twins, it is evident that they hold immense potential and practical value in enhancing production efficiency, reducing costs, and improving product quality. However, achieving widespread adoption and deep integration of digital twins and intelligent algorithms in smart manufacturing requires addressing a series of challenges, including data management, model construction, real-time performance, security, and privacy. Looking ahead, as technology continues to evolve and innovate, smart manufacturing systems integrating digital twins and intelligent algorithms will become increasingly intelligent, efficient, and reliable, providing stronger support for the transformation and upgrading of the manufacturing industry.

Looking forward, it is essential to emphasize the growing importance of cross-disciplinary collaboration to overcome the existing limitations in digital twin and intelligent algorithm integration. The convergence of fields such as data science, cyber-physical systems, and manufacturing engineering will drive the next wave of innovation in smart manufacturing. Additionally, future research should focus on enhancing the adaptability and learning capabilities of intelligent algorithms to better cope with the dynamic and uncertain nature of manufacturing processes. The advancement of edge computing and 5G technologies also promises to significantly improve real-time responsiveness and data security, further strengthening the practical value of digital twins. Ultimately, the sustained development and deployment of these technologies will not only promote operational excellence but also contribute to more sustainable and resilient manufacturing ecosystems, aligning with broader industry and societal goals.

References

[1] Xiang, C., & Li, B. (2020). Research on ship intelligent manufacturing data monitoring and quality control system based on industrial Internet of Things. International Journal of Advanced Manufacturing Technology, 107(3–4), 983–992. DOI:10.1007/s00170-019-04208-w

[2] Liu, X., & Zhou, Q. (2021). Intelligent manufacturing system based on data mining algorithm. International Journal of Grid and Utility Computing, 12(4), 396–405. DOI:10.1504/IJGUC.2021.119573

[3] Nadanakumar, M., & Parthiban, P. (2023). Fuzzy based supply chain management system for intelligent manufacturing prioritization of boiler insulation items. Journal of Data, Information and Management, 5(3), 165–175. DOI:10.1007/s42488-023-00095-9

[4] Wang, Y., Li, G., Chen, J., & Zhang, Z. (2020). Application of Fuzzy Analytic Hierarchy Process in Intelligent Manufacturing Resources Allocation Evaluation System of Alliance Enterprises. Journal of Physics: Conference Series, 1605(1), 12038. DOI:10.1088/1742-6596/1605/1/012038

[5] Li, X., Huang, Z., & Ning, W. (2023). Intelligent manufacturing quality prediction model and evaluation system based on big data machine learning. Computers and Electrical Engineering, 111(Pt.A), 108904–108911. DOI:10.1016/j.compeleceng.2023.108904

[6] He, Y., Zhao, Y., Han, X., Zhou, D., & Wang, W. (2020). Functional risk-oriented health prognosis approach for intelligent manufacturing systems. Reliability Engineering and System Safety, 203. DOI:10.1016/j.ress.2020.107090

[7] Su, Y., Gai, Y. hua, & Lv, Q. ying. (2022). Enterprise Cluster Intelligent Manufacturing Information Management System Based on Wireless Communication Technology. Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST, 414 LNICST, 200–211. DOI:10.1007/978-3-030-94185-7_14

[8] Yan, H., Yang, J., & Wan, J. (2020). KnowIME: A System to Construct a Knowledge Graph for Intelligent Manufacturing Equipment. IEEE Access, 8, 41805–41813. DOI:10.1109/ACCESS.2020.2977136

[9] Wang, X. (2021). Design of customized intelligent manufacturing information interaction system based on virtual technology. Journal of Physics: Conference Series, 2074(1). DOI:10.1088/1742-6596/2074/1/012043

[10] Zhang, Z., Zhu, Z., Zhang, J., & Wang, J. (2022). Construction of intelligent integrated model framework for the workshop manufacturing system via digital twin. International Journal of Advanced Manufacturing Technology, 118(9–10), 3119–3132. DOI:10.1007/s00170-021-08171-3

[11] Huang, X. (2020). Intelligent remote monitoring and manufacturing system of production line based on industrial Internet of Things. Computer Communications, 150, 421–428. DOI:10.1016/j.comcom.2019.12.011

[12] Suleykin, A., Bakhtadze, N., Elpashev, D., & Pyatetsky, V. (2022). Associative Rules-Driven Intelligent Production Schedule Control System for Digital Manufacturing Ecosystem. IFAC-PapersOnLine, 55(10), 2526–2532. DOI:10.1016/j.ifacol.2022.10.089

[13] Sobchuk, V. V., Zamrii, I. V., Barabash, O. V., & Musienko, A. P. (2021). Methodology for building a functionally stable intelligent information system of a manufacturing enterprise. Bulletin of the Taras Shevchenko National University of Kyiv. Physics and Mathematics, 2021(4), 116–127. DOI:10.17721/1812-5409.2021/4.18

[14] Carla Acosta, P., Terán, H. C., Arteaga, O., & Terán, M. B. (2020). Machine learning in intelligent manufacturing system for optimization of production costs and overall effectiveness of equipment in fabrication models. Journal of Physics: Conference Series, 1432(1), 012085-. DOI:10.1088/1742-6596/1432/1/012085

[15] Guo, D., Li, M., Zhong, R., & Huang, G. Q. (2021). Graduation Intelligent Manufacturing System (GiMS): an Industry 4.0 paradigm for production and operations management. Industrial Management and Data Systems, 121(1), 86–98. DOI:10.1108/IMDS-08-2020-0489

[16] Shi, M. (2021). Knowledge Graph Question and Answer System for Mechanical Intelligent Manufacturing Based on Deep Learning. Mathematical Problems in Engineering, 2021. DOI:10.1155/2021/6627114

[17] Nguyen, T. D., Chau, T. T., & Do, T. K. L. (2023). Designing and Manufacturing a Vacuum Frying System with Intelligent Controlling. Journal of Technical Education Science, 77, 10–20. DOI:10.54644/jte.77.2023.1374

[18] Yuan, Y. (2023). Research on Intelligent Manufacturing Flexible Production Line System Based on Industrial Robot. 2023 IEEE International Conference on Control, Electronics and Computer Technology, ICCECT 2023, 325–329. DOI:10.1109/ICCECT57938.2023.10141442

[19] Wang, X., Wang, Q., & Zhao, Y. (2021). Individual adoption of ERP system in intelligent manufacturing supply chain based on system dynamics. ACM International Conference Proceeding Series. DOI:10.1145/3465631.3465677

[20] Guo, Y., Qin, Q., Zhang, W., Wei, Y., & Li, W. (2023). Evaluation model and algorithm of intelligent manufacturing system based on pattern recognition and big data. Soft Computing, 27(7), 4195–4208. DOI:10.1007/s00500-022-07030-x

[21] Wu, Q., Mao, Y., Chen, J., & Wang, C. (2021). Application research of digital twin-driven ship intelligent manufacturing system: Pipe machining production line. Journal of Marine Science and Engineering, 9(3), 338. DOI:10.3390/jmse9030338

[22] Simeone, A., Zeng, Y., & Caggiano, A. (2021). Intelligent decision-making support system for manufacturing solution recommendation in a cloud framework. International Journal of Advanced Manufacturing Technology, 112(3–4), 1035–1050. DOI:10.1007/s00170-020-06389-1

[23] Liang, G., Chen, F., Liang, Y., Feng, Y., Wang, C., & Wu, X. (2021). A Manufacturing-Oriented Intelligent Vision System Based on Deep Neural Network for Object Recognition and 6D Pose Estimation. Frontiers in Neurorobotics, 14. DOI:10.3389/fnbot.2020.616775

[24] Fan, L., & Zhang, L. (2022). Multi-system fusion based on deep neural network and cloud edge computing and its application in intelligent manufacturing. Neural Computing and Applications, 34(5), 3411–3420. DOI:10.1007/s00521-021-05735-y

[25] Xu, C., & Zhu, G. (2021). Intelligent manufacturing Lie Group Machine Learning: real-time and efficient inspection system based on fog computing. Journal of Intelligent Manufacturing, 32(1), 237–249. DOI:10.1007/s10845-020-01570-5

[26] Ionel, R. D. S., Lamanna, G., & Opran, C. G. (2022). Intelligent Link between Lean Manufacturing and the Cyber-Physical Industry 4.0 System. Macromolecular Symposia, 404(1). DOI:10.1002/masy.202100478

[27] Liu, C., Tang, D., Zhu, H., & Nie, Q. (2021). A novel predictive maintenance method based on deep adversarial learning in the intelligent manufacturing system. IEEE Access, 9(99), 49557–49575. DOI:10.1109/ACCESS.2021.3069256

[28] Cronin, C., Awasthi, A., Conway, A., O'Riordan, D., & Walsh, J. (2020). Design and development of a material handling system for an autonomous intelligent vehicle for flexible manufacturing. Procedia Manufacturing, 51, 493–500. DOI:10.1016/j.promfg.2020.10.069

[29] Guo, D., Li, M., Ling, S., Zhong, R. Y., Rong, Y., & Huang, G. Q. (2021). Synchronization-oriented reconfiguration of FPAI under graduation intelligent manufacturing system in the COVID-19 pandemic and beyond. Journal of Manufacturing Systems, 60(60-), 893–902. DOI:10.1016/j.jmsy.2021.05.017

[30] Ren, J., Zhang, L., Feng, Y., & Wan, L. (2021). An online detection system of energy efficiency for intelligent manufacturing. Energy Reports, 7, 1363–1368. DOI:10.1016/j.egyr.2021.09.126

[31] Mo, J. P. T., & Beckett, R. C. (2022). Transdisciplinary system of systems development in the trend to X4.0 for intelligent manufacturing. International Journal of Computer Integrated Manufacturing, 35(1), 21–35. DOI:10.1080/0951192X.2021.1992663

[32] Qin, Y., Wang, M., & Li, M. (2023). Research on the Training of Interdisciplinary-Based Intelligent Manufacturing Talents. Journal of Contemporary Educational Research, 7(2), 15–22. DOI:10.26689/jcer.v7i2.4700

[33] Chen, M. Y., Lughofer, E. D., & Egrioglu, E. (2022). Deep learning and intelligent system towards smart manufacturing. Enterprise Information Systems, 16(2), 189–192. DOI:10.1080/17517575.2021.1898050

[34] Guo, D., Zhong, R. Y., Lin, P., Lyu, Z., Rong, Y., & Huang, G. Q. (2020). Digital twin-enabled Graduation Intelligent Manufacturing System for fixed-position assembly islands. Robotics and Computer-Integrated Manufacturing, 63. DOI:10.1016/j.rcim.2019.101917

[35] Guo, Y., Zhang, W., Qin, Q., Chen, K., & Wei, Y. (2023). Intelligent manufacturing management system based on data mining in artificial intelligence energy-saving resources. Soft Computing, 27(7), 4061–4076. DOI:10.1007/s00500-021-06593-5

[36] Wang, S., Xu, Z., Wu, C., Hua, L., & Zhu, D. (2023). Towards region-based robotic machining system from perspective of intelligent manufacturing: A technology framework with case study. Journal of Manufacturing Systems, 70, 451–463. DOI:10.1016/j.jmsy.2023.08.017

[37] Guo, Y., Wang, N., Xu, Z. Y., & Wu, K. (2020). The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology. Mechanical Systems and Signal Processing, 142, 106630. DOI:10.1016/j.ymssp.2020.106630

[38] Sun, M., Cai, Z., & Zhao, N. (2023). Design of intelligent manufacturing system based on digital twin for smart shop floors. International Journal of Computer Integrated Manufacturing, 36(4), 542–566. DOI:10.1080/0951192X.2022.2128212

[39] Feng, C. (2023). Research on Real-Time Dynamic Scheduling Mechanism of Intelligent Manufacturing System Based on Agent. International Journal of Science and Engineering Applications. DOI:10.7753/ijsea1208.1030

[40] Wang, Z., Cui, L., Guo, W., Zhao, L., Yuan, X., Gu, X., Tang, W., Bu, L., & Huang, W. (2022). A design method for an intelligent manufacturing and service system for rehabilitation assistive devices and special groups. Advanced Engineering Informatics, 51, 101504-. DOI:10.1016/j.aei.2021.101504

[41] Yang, J., Liu, H., Gu, J., Gou, Y., Chen, X., & You, S. (2023). Construction of practical teaching system for intelligent manufacturing specialty under the background of double innovation. Journal of Education, Humanities and Social Sciences, 14, 1–5. DOI:10.54097/ehss.v14i.8788

[42] Liu, Z., & Pu, J. (2022). Analysis and research on intelligent manufacturing medical product design and intelligent hospital system dynamics based on machine learning under big data. Enterprise Information Systems, 16(2), 193–207. DOI:10.1080/17517575.2019.1701713

[43] Wang, S., Meng, J., Xie, Y., Jiang, L., Ding, H., & Shao, X. (2023). Reference training system for intelligent manufacturing talent education: platform construction and curriculum development. Journal of Intelligent Manufacturing, 34(3), 1125–1164. DOI:10.1007/s10845-021-01838-4

[44] Kang, Y. Y., Feng, G. F., & Sun, J. (2020). A Health Status Assessment Approach of Intelligent Manufacturing System based on Fuzzy Analytic Hierarchy Process. IOP Conference Series: Materials Science and Engineering, 825(1), 012020 (6pp). DOI:10.1088/1757-899X/825/1/012020

[45] Li, Y., Zhang, Q., Xu, H., Lim, E., & Sun, J. (2022). Virtual monitoring system for a robotic manufacturing station in intelligent manufacturing based on Unity 3D and ROS. Materials Today: Proceedings, 70, 24–30. DOI:10.1016/j.matpr.2022.08.486

[46] Wang, Z. H., Li, Y. T., & Wu, Y. C. (2023). Design of intelligent manufacturing IoT sensing system for polymer process monitoring. International Journal of Advanced Manufacturing Technology, 129(7–8), 2933–2947. DOI:10.1007/s00170-023-12510-x

[47] Lai, Z. H., Tao, W., Leu, M. C., & Yin, Z. (2020). Smart augmented reality instructional system for mechanical assembly towards worker-centered intelligent manufacturing. Journal of Manufacturing Systems, 55, 69–81. DOI:10.1016/j.jmsy.2020.02.010

[48] Liu, Z. feng, Zhang, Y. ze, Yang, C. bin, Huang, Z. guang, Zhang, C. xia, & Xie, F. gui. (2022). Generalized distributed four-domain digital twin system for intelligent manufacturing. Journal of Central South University, 29(1), 209–225. DOI:10.1007/s11771-022-4926-8

[49] Kong, L., & Ma, B. (2022). Retraction Note: Intelligent manufacturing model of construction industry based on Internet of Things technology. International Journal of Advanced Manufacturing Technology, 123(7–8), 2961. DOI:10.1007/s00170-022-10417-7

[50] Wu, X., Yan, B., Xue, C., & Xu, P. (2021). Information presentation of intelligent manufacturing production line information system based on gravity model. Dongnan Daxue Xuebao (Ziran Kexue Ban)/Journal of Southeast University (Natural Science Edition), 51(1), 145–152. DOI:10.3969/j.issn.1001-0505.2021.01.020

[51] Jahed, A., & Moghaddam, R. T. (2021). Mathematical modeling for a flexible manufacturing scheduling problem in an intelligent transportation system. Iranian Journal of Management Studies, 14(1), 189–208. DOI:10.22059/IJMS.2020.261618.673203

[52] Liu, Q., Li, X., & Gao, L. (2021). A Novel MILP Model Based on the Topology of a Network Graph for Process Planning in an Intelligent Manufacturing System. Engineering, 7(6), 807–817. DOI:10.1016/j.eng.2021.04.011

[53] Zhu, Q., Huang, S., Wang, G., Moghaddam, S. K., Lu, Y., & Yan, Y. (2022). Dynamic reconfiguration optimization of intelligent manufacturing system with human-robot collaboration based on digital twin. Journal of Manufacturing Systems, 65, 330–338. DOI:10.1016/j.jmsy.2022.09.021

[54] Zhou, J., & Wen, X. (2022). The Dynamics of Manufacturing Value Chain Climbing System under MPL Framework: Modeling and Simulation Based on Intelligent Transformation. Discrete Dynamics in Nature and Society, 2022(Pt.5). DOI:10.1155/2022/4574183

[55] Goswami, M., Daultani, Y., Chan, F. T. S., & Pratap, S. (2022). Assessing the impact of supplier benchmarking in manufacturing value chains: an Intelligent decision support system for original equipment manufacturers. International Journal of Production Research, 60(24), 7411–7435. DOI:10.1080/00207543.2022.2075811

[56] Lu, S., Liu, S., Zhu, Y., Liang, W., Li, K., & Lu, Y. (2023). A DRL-Based Decentralized Computation Offloading Method: An Example of an Intelligent Manufacturing Scenario. IEEE Transactions on Industrial Informatics, 19(9), 9631–9641. DOI:10.1109/TII.2022.3227652

[57] Ben Hassen, D., Ben Jdidia, A., Hentati, T., Abbes, M. S., & Haddar, M. (2023). A novel intelligent reasoning method to estimate the cutting system energy consumption for a sustainable manufacturing. Journal of the Chinese Institute of Engineers, Transactions of the Chinese Institute of Engineers,Series A, 46(1), 74–80. DOI:10.1080/02533839.2022.2141337

[58] Zhou, C., & Cao, Q. (2023). Retraction Note: Design and implementation of intelligent manufacturing project management system based on bill of material (Cluster Computing, (2019), 22, S4, (8647-8655), 10.1007/s10586-018-1934-4). Cluster Computing, 26(Suppl 1), 91. DOI:10.1007/s10586-022-03876-w

[59] Altıparmak, S. C., Yardley, V. A., Shi, Z., & Lin, J. (2022). Extrusion-based additive manufacturing technologies: State of the art and future perspectives. Journal of Manufacturing Processes, 83(ptaa), 607–636. DOI:10.1016/j.jmapro.2022.09.032

[60] Wang, J., Mohamed, Y., Han, S., Li, X., & Al-Hussein, M. (2022). 3D ergonomics-based motion-level productivity analysis for intelligent manufacturing in industrialized construction. Canadian Journal of Civil Engineering, 50(3), 197–209. DOI:10.1139/cjce-2022-0090

[61] Dai, L., & Liu, J. (2022). Construction of intelligent manufacturing experimental platform for artificial intelligence technology. Proceedings of SPIE, 12289(000), 8. DOI:10.1117/12.2640687

[62] Liu, Q., Liu, M., Zhou, H., Yan, F., Ma, Y., & Shen, W. (2022). Intelligent manufacturing system with human-cyber-physical fusion and collaboration for process fine control. Journal of Manufacturing Systems, 64, 149–169. DOI:10.1016/j.jmsy.2022.06.004

[63] Nagy, L., Ruppert, T., Löcklin, A., & Abonyi, J. (2022). Hypergraph-based analysis and design of intelligent collaborative manufacturing space. Journal of Manufacturing Systems, 65, 88–103. DOI:10.1016/j.jmsy.2022.08.001

[64] Wang, C. Y., Huang, C. Y., & Chiang, Y. H. (2022). Solutions of Feature and Hyperparameter Model Selection in the Intelligent Manufacturing. Processes, 10(5). DOI:10.3390/pr10050862

[65] Qian, D., Yang, T., Jiang, L., & Liu, P. (2022). Design of controlling program of intelligent warehouse management system based on flexible manufacturing. Proceedings of SPIE, 12332(000), 66. DOI:10.1117/12.2652985

[66] Wang, X., & Zeng, G. (2022). Intelligent Control of Cabin Environment Using Computational Fluid Dynamics for Intelligent Manufacturing. Fluid Dynamics and Materials Processing, 18(3), 563–576. DOI:10.32604/fdmp.2022.017884

[67] Zhang, Z., Zhao, R., Zhang, H., Zhu, W., Jia, P., Li, C., & Ma, Y. (2023). Variable-Weighted Error Propagation Model of a Ultra-Wide-Band Indoor Positioning System in an Intelligent Manufacturing Lab. Applied Sciences (Switzerland), 13(14). DOI:10.3390/app13148400

[68] Pang, J., Dai, J., & Li, Y. (2022). An Intelligent Fault Analysis and Diagnosis System for Electromagnet Manufacturing Process Based on Fuzzy Fault Tree and Evidence Theory. Mathematics, 10(9). DOI:10.3390/math10091437

[69] Sauer, W., Weigert, G., & Hampel, D. (2023). an Open Optimization System for Controlling of Manufacturing Processes. Proceeding of Flexible Automation and Intelligent Manufacturing, 1997, 261–268. DOI:10.1615/faim1997.250

[70] Hassan, N. M., Hamdan, A., Shahin, F., Abdelmaksoud, R., & Bitar, T. (2023). An artificial intelligent manufacturing process for high-quality low-cost production. International Journal of Quality and Reliability Management, 40(7), 1777–1794. DOI:10.1108/IJQRM-07-2022-0204

[71] Eddy, D., White, M., & Blanchette, D. (2023). Intelligent Insights for Manufacturing Inspections from Efficient Image Recognition †. Machines, 11(1). DOI:10.3390/machines11010045

[72] Chai, T., Liu, Q., Ding, J., Lu, S., Song, Y., & Zhang, Y. (2022). Perspectives on industrial-internet-driven intelligent optimized manufacturing mode for process industries. Zhongguo Kexue Jishu Kexue/Scientia Sinica Technologica, 52(1), 14–25. DOI:10.1360/SST-2021-0405

[73] Koduru, J. P., Narayana, K. L., & Mantrala, K. M. (2022). Hybrid swarm-based intelligent algorithm for lattice structure optimization in additive manufacturing system. International Journal on Interactive Design and Manufacturing, 16(4), 1511–1524. DOI:10.1007/s12008-022-00863-8

[74] Ullah, A., & Younas, M. (2024). Development and Application of Digital Twin Control in Flexible Manufacturing Systems. Journal of Manufacturing and Materials Processing, 8(5). DOI:10.3390/jmmp8050214

[75] Vitorino, J., Ribeiro, E., Silva, R., Santos, C., Carreira, P., Mitchell, G. R., & Mateus, A. (2019). Industry 4.0 - Digital Twin Applied to Direct Digital Manufacturing. Applied Mechanics and Materials, 890, 54–60. DOI:10.4028/www.scientific.net/amm.890.54

[76] Hürkamp, A., Lorenz, R., Ossowski, T., Behrens, B. A., & Dröder, K. (2021). Simulation-based digital twin for the manufacturing of thermoplastic composites. Procedia CIRP, 100, 1–6. DOI:10.1016/j.procir.2021.05.001

[77] Liu, X., Jiang, Y., Wang, Z., Zhong, R. Y., Cheung, H. H., & Huang, G. Q. (2023). imseStudio: blockchain-enabled secure digital twin platform for service manufacturing. International Journal of Production Research, 61(12), 3984–4003. DOI:10.1080/00207543.2021.2003462