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Integration of Artificial Intelligence and Digital Twins for Real-Time Control in Smart Manufacturing

Chinmay Patil
Skydio Inc.,
Hayward, CA, USA

Sarang Kamalakar
Parentheses Systems
Pune, India.

Abstract:
The rapid evolution of smart manufacturing necessitates innovative approaches for real-time monitoring, control, and optimization of production processes. Artificial Intelligence (AI) and Digital Twins (DT) have emerged as transformative technologies capable of enhancing operational efficiency, predictive maintenance, quality assurance, and adaptive process control. This paper presents a comprehensive framework for integrating AI with digital twin systems to enable real-time manufacturing control. The study reviews current methodologies, architectures, and use cases, highlights the key capabilities and benefits of AI-enabled digital twins, and discusses practical challenges and implementation considerations. Additionally, schematic representations of system architecture, data flow, and closed-loop control are provided to guide practitioners and researchers. The findings suggest that the integration of AI and digital twins significantly enhances manufacturing responsiveness, flexibility, and overall performance while offering a foundation for future manufacturing systems.

Keywords: Artificial Intelligence, Digital Twin, Real-Time Manufacturing Control, Smart Manufacturing, Predictive Maintenance, Process Optimization.

I. INTRODUCTION

Modern manufacturing environments are characterized by increasing complexity, rapid product cycles, and high variability in production demand. Traditional control methods, reliant on static schedules and manual intervention, are insufficient to handle dynamic disturbances, equipment degradation, or variable material properties. To address these challenges, advanced technologies such as Artificial Intelligence (AI) and Digital Twins (DT) are being deployed to enable adaptive, predictive, and real-time control of manufacturing processes [1]–[3].

A digital twin is a virtual replica of a physical system that synchronizes with real-time data to model, simulate, and predict operational states [4]. When coupled with AI algorithms—including machine learning, deep learning, and reinforcement learning—digital twins evolve from passive representations into active decision-making systems capable of optimizing performance, detecting anomalies, and enabling autonomous control [5], [6].

The purpose of this paper is to provide a comprehensive overview of AI-enabled digital twins in manufacturing, emphasizing real-time control applications. The contributions of this paper include:

1. Reviewing current AI and digital twin technologies in manufacturing.
2. Presenting a layered architecture for real-time control.
3. Highlighting use cases and potential benefits.
4. Discussing practical challenges and providing recommendations for implementation.

II. BACKGROUND

A. Digital Twins in Manufacturing

Digital twins in manufacturing serve as virtual counterparts of machines, production lines, or entire factories. By continuously ingesting sensor data, production logs, and environmental variables, a digital twin reflects the real-time operational state of its physical counterpart [7]. Beyond monitoring, digital twins enable simulation, scenario analysis, and predictive evaluation of process changes, thereby supporting decision-making and process optimization [8].

Applications include workflow optimization, equipment performance analysis, virtual commissioning, and production planning. For example, a factory digital twin can simulate machine idle times, bottlenecks, and material flow to identify and resolve inefficiencies [9].

B. Artificial Intelligence in Manufacturing

AI encompasses computational techniques that allow systems to learn from data, identify patterns, make predictions, and execute decisions [10]. In manufacturing, AI applications span:

- **Predictive maintenance:** forecasting machine failure based on historical and sensor data.
- **Quality control:** detecting defects in real time through computer vision and statistical learning.
- **Process optimization:** dynamically adjusting parameters and apply mean shift to process parameters, such as feed rate, temperature, or machine speed.
- **Scheduling and resource allocation:** adapting production schedules based on real-time constraints [11], [12].

C. Synergy of AI and Digital Twins

While digital twins provide a high-fidelity model of the manufacturing system, AI equips the twin with predictive and prescriptive capabilities. Integration allows for:

1. **Real-time decision-making:** AI algorithms analyze live twin data to recommend or execute corrective actions.
2. **Predictive analytics:** Forecasting equipment degradation, process deviations, or quality defects.
3. **Process optimization:** Evaluating multiple scenarios virtually before applying optimal solutions.
4. **Autonomous control :** Closed-loop adaptation of system parameters with minimal human intervention [13].

Architecture for real time manufacturing control

A robust AI-enabled digital twin system for real-time control typically follows a **layered architecture**

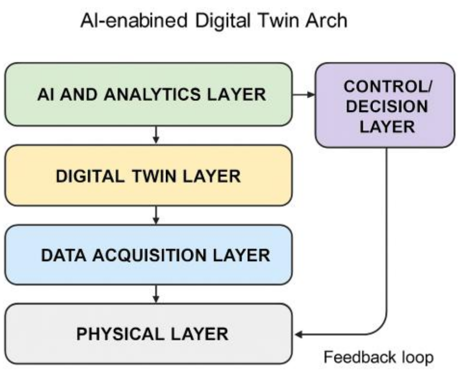

Fig. 1: AI-enabled Digital Twin Architecture for Real-Time Manufacturing Control.

Physical Layer: The Physical Layer is the bottom-most layer in industrial and IoT architectures. Its primary function is to interact directly with the physical environment—measuring conditions, performing actions, and enabling machines to execute manufacturing processes. Physical layer examples include sensors, actuators, robots, torque tools, joining tools and various machine tools generating real-time operational data.

Data Acquisition Layer: The Data Acquisition Layer (DAL) is responsible for collecting, conditioning, and preparing raw data from the Physical Layer before it's transmitted to higher-level systems. Its main purpose is to ensure that data is accurate, relevant, and usable for real-time monitoring, control, and simulation. Adding SCADA (Supervisory Control and Data Acquisition) to the Data Acquisition Layer brings significant benefits because SCADA acts as both a data collection system and a supervisory control interface for industrial processes. SCADA systems can also be leveraged for generating human machine interfaces.

Digital Twin Layer: The Digital Twin Layer sits above the Data Acquisition Layer, receiving real-time data from sensors, machines, and SCADA systems, and using it to mirror the current state of the physical system. Maintains a virtual model of the physical system, updating its state based on incoming data. Simulations, scenario testing, and predictive modeling are performed here.

AI and Analytics Layer: Implements machine learning, deep learning, or reinforcement learning models to predict system states, optimize process parameters, and detect anomalies. This layer in modern architecture transforms raw and processed operational data into actionable intelligence. By integrating with digital twins, it allows virtual "what-if" simulations to evaluate process changes without impacting physical operations. Overall, this layer empowers factories to move from reactive operations to smart, self-aware, and data-driven manufacturing ecosystems, enhancing productivity, reducing downtime, and supporting continuous improvement.

Control/Decision Layer: Serves as the bridge between analytical insights and physical action in industrial systems and digital twin architectures. It takes the predictions, optimizations, and anomaly detections generated by the AI and Analytics Layer and translates them into actionable commands for machines or actionable recommendations for human operators. For example, it can automatically fine-tune robotic arm movements, adjust conveyor speeds, or modify torque settings to prevent defects, while simultaneously alerting operators to critical issues or suggested interventions.

Feedback Loop: Updated physical system data is continuously fed back into the twin, completing the real-time control cycle [14], [15]. This continuous synchronization allows the AI and Analytics Layer to detect deviations, predict potential issues, and optimize processes based on the most recent conditions. The Control/Decision Layer then uses these insights to adjust machine operations or provide operator recommendations, which in turn influence the physical system. As updated data flows back into the twin, the loop repeats, creating a closed-loop system that enables ongoing monitoring, proactive maintenance, dynamic optimization, and rapid response to changing conditions. This cycle ensures that both the physical and digital systems remain aligned, fostering resilient, efficient, and self-correcting operations in real time.

III. IMPLEMENTATION FRAMEWORK

Deploying an AI-enabled digital twin for real-time manufacturing control requires a structured approach encompassing objectives, data infrastructure, model development, integration, and continuous improvement.

Define Objectives and Use-Cases

Defining measurable goals ensures that the digital twin delivers actionable insights [16]. Some examples of these measurable goals are indicated in Table 1

Table 1: Goals and measurable metrics

Goal / Objective	Metric	Target / Measurement unit examples
Increase Production Efficiency	Cycle Time	< Y minutes per cycle
	Machine Utilization	> 85% uptime
Reduce Downtime	Mean Time Between Failures (MTBF)	> A hours
	Mean Time to Repair (MTTR)	< B minutes
Improve Product Quality	First Pass Yield (FPY)	> 95%
	Process Variability	Within ± X% of setpoint/ Cpk target of 1.33 or greater
Resource Usage	Resource Utilization	> 85% efficient
Enhance Predictive Maintenance	Predictive Accuracy	> 90% correct predictions
	Anomaly Detection Rate	> 95% detected anomalies
	Remaining Useful Life (RUL) Forecast	Accurate within ±X days

Data Infrastructure

The Data Infrastructure forms the backbone of any digital twin and AI analytics ecosystem, ensuring that data flows seamlessly, reliably, and securely across all layers of the system. A robust data pipeline begins at the shop floor with IoT-enabled sensors, actuators, and programmable logic controllers (PLCs) that continuously capture real-time operational data. This data is then transmitted through edge computing devices, factory network or other options, performing initial filtering, aggregation, and preprocessing close to the source to reduce latency and network load. The infrastructure must also integrate with higher-level enterprise systems such as Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) platforms to connect operational data with production planning, inventory, and business processes. To ensure reliability and traceability, all data must be accurate, time-stamped, and assigned a unique transaction identifier, enabling synchronization between physical and digital environments [17]. Furthermore, preprocessing—such as noise removal, normalization, and formatting—is essential to make the data ready for AI and machine learning models, which depend on clean, structured, and context-rich inputs. Together, these elements create a scalable and intelligent data infrastructure that supports real-time decision-making and continuous optimization in modern smart factories.

Digital Twin Development

The digital twin must replicate the physical system including machine dynamics, material flow, environmental interactions, and stochastic events. Hybrid simulation models (discrete-event and continuous) are often employed. Crucially, the digital twin's reliability depends on model validation and continuous calibration [18]. Validation ensures that the simulated behavior aligns closely with real-world data collected from sensors and IoT devices, while calibration involves ongoing fine-tuning of parameters as conditions change in the physical system. Through this iterative process, the digital twin remains a reasonably accurate, real-time representation of the physical system, capable of supporting predictive analytics, optimization, and scenario testing for smarter, data-driven decision-making. However, it's important to recognize that some degree of inaccuracy is inevitable, as the model is built on assumptions, simplifications, and estimated parameters that cannot capture every detail of real-world variability.

Despite these limitations, a well-calibrated digital twin provides the most practical and insightful approximation available, offering valuable guidance for operational improvement, risk assessment, and strategic planning.

AI Model Integration

AI Model Integration is a crucial phase in enhancing the intelligence and adaptability of a digital twin. In this stage, various artificial intelligence and machine learning models are embedded directly into the twin's architecture to transform it from a passive simulation tool into an active, decision-support and self-optimizing system. These models operate on data continuously streamed from the physical system, allowing the twin to learn, predict, and adapt in real time.

Different categories of AI models serve distinct purposes: supervised learning models are trained on labeled historical data to predict system states such as equipment failures, product quality outcomes, or energy usage patterns; unsupervised learning models detect hidden patterns, correlations, and anomalies within large datasets without predefined labels, which is particularly useful for identifying unusual operating conditions or sensor drift; and reinforcement learning algorithms learn optimal control policies through trial-and-error interaction with the simulated environment, helping to fine-tune machine parameters, scheduling, or resource allocation strategies. Additionally, optimization algorithms—such as genetic algorithms or gradient-based methods—help determine the most efficient operating configurations, balancing productivity, cost, and quality objectives.

Once integrated, these AI models enable the digital twin to not only mirror the physical system but also anticipate future states, recommend or automatically implement corrective actions, and continuously improve performance. To maintain accuracy and relevance, continuous retraining and model updating are essential, allowing the AI to adapt to changing operational conditions, new sensor data, and system modifications. While the models may not always perfectly capture complex real-world dynamics, their integration significantly enhances the twin's analytical and prescriptive capabilities, making it a powerful tool for predictive maintenance, process optimization, and intelligent decision-making in dynamic industrial environments [19].

Control and Feedback Loops

In practice, control execution can occur in two modes [20]:

- Autonomous control, where the system automatically adjusts machine parameters (e.g., speed, torque, temperature, or flow rate) through direct integration with Programmable Logic Controllers (PLCs) or Distributed Control Systems (DCS). This mode is typically used for high-speed or repetitive processes where rapid response is essential and operator intervention could introduce delays.
- Operator-assisted control, where AI-generated recommendations are presented through Human-Machine Interfaces (HMI) or Supervisory Control and Data Acquisition (SCADA) systems. In this case, the operator reviews, validates, and authorizes actions—ideal for complex or safety-critical operations that require human oversight.

Feedback loop ensures that the results of these actions are continuously monitored and evaluated. Real-time sensor data is sent back to the digital twin and AI models as explained in Fig 2. This live feedback allows the system to assess whether control actions resulted in intended outcomes and, if necessary, apply adjustments to maintain optimal performance. For example, if a robotic arm deviates from its expected trajectory, the twin detects this discrepancy, the AI model predicts the corrective control sequence, and the PLC implements micro-adjustments to restore precision.

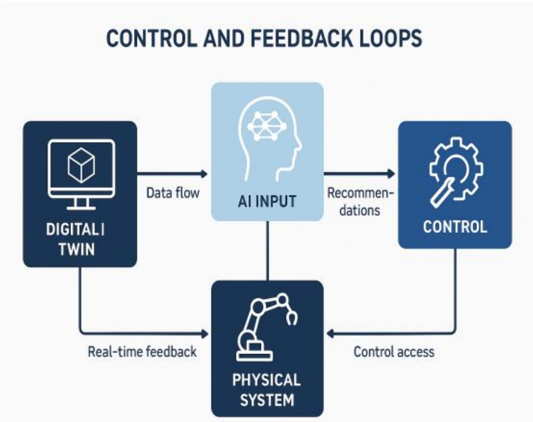

Fig 2: Adaptive control through continuous feedback and AI insights.

Pilot Testing and Scaling

Pilot Testing and Scaling is a critical phase in the deployment of digital twin and AI analytics systems, ensuring that the technology delivers measurable value before full-scale implementation. It provides a structured, low-risk approach to validate technical feasibility, performance accuracy, and operational impact within a controlled environment—typically on a single production line, machine, or process unit.[21]. In Pilot testing, beyond metrics discussed in Table 1., also consider use of metrics from table 2.

Table 2: Pilot testing validation metrics

Predictive and AI Model Performance Metrics		
Metric	**Purpose**	**Typical Limit / Target**
Prediction Accuracy	Verifies the reliability of AI-based forecasts (e.g., failure, demand).	≥ 90% accuracy
Anomaly Detection Precision/Recall	Measures how accurately the AI identifies faults or abnormal conditions.	≥ 95% precision, ≥ 90% recall
False Alarm Rate	Assesses the usability of AI alerts for operators.	< 5% false positives
Model Latency (Decision Delay)	Ensures timely responses to real-time data.	< 500 ms for edge or on-prem inference
Model Drift / Retraining Interval	Evaluates model stability and data evolution over time.	Drift < 2–3% between retrain cycles
Digital Twin Model Fidelity Metrics		
Simulation Accuracy (Deviation vs. Real Data)	Assesses how closely the twin mirrors real system behavior.	±3–5% deviation
Data Latency (Physical → Digital Update)	Measures synchronization quality between real and virtual systems.	< 1 second for critical loops
Model Calibration Frequency	Ensures alignment over operational cycles.	Monthly or after significant process change
Twin System Uptime	Verifies twin system availability and stability.	> 99% uptime during pilot

Human and Integration Metrics		
Operator Acceptance Rate	Gauges human-machine collaboration success.	≥ 80% positive feedback
System Integration Success	Assesses connection with MES, ERP, and legacy control systems.	≥ 95% successful API or protocol integration
Training Completion and Competence	Ensures workforce readiness for scaled deployment.	100% completion with ≥ 90% competency assessment score
Safety Compliance Incidents	Validates operational safety and system reliability.	Zero incidents during pilot phase

IV. USE CASES

A. Predictive maintenance

By analyzing sensor data (vibration, temperature, and load), AI models integrated with digital twins can predict failures before they occur. This reduces unplanned downtime and extends equipment life [22]. As an example - in an automotive assembly line, robotic welding cells are critical for assembling car body panels. Unplanned robot failures can halt production, increase costs, and disrupt schedules.

By leveraging AI and digital twins, manufacturers can predict and prevent these failures, optimizing both robot performance and maintenance planning. Each robot cell is represented by a digital twin that receives real-time sensor data, including motor currents, joint positions, torque, vibration, and temperature. AI analyzes historical and live data to forecast issues such as motor fatigue, joint misalignment, or gripper wear, while simulations in the digital twin allow engineers to test different production loads and adjust operating parameters to reduce wear. Maintenance alerts are integrated with the Manufacturing Execution System to minimize production disruption. This approach will potentially reduce unplanned downtime—from 12 to 2–3 hours per month per cell—increases production throughput by 5–8%, lowers maintenance costs by 25–35%, and extends the lifespan of the consumables in robotic equipment.

B. Dynamic process optimization

Real-time adjustment of machine parameters (speed, feed rate, temperature) based on twin simulations allows for optimization under varying conditions, improving throughput and minimizing energy consumption [23]. An illustration of this approach would be: In an automotive assembly plant, the final paint shop applies multiple layers of primer, base coat, and clear coat to car bodies. Variations in ambient temperature, humidity, and paint viscosity can affect drying time, coating thickness, and overall quality. By implementing dynamic process optimization using AI and digital twins, the plant can adjust machine parameters in real time to maintain consistent quality and efficiency.

Each paint booth has a digital twin that models the robotic sprayers, conveyor speed, oven temperature, and environmental conditions. Real-time sensor data—including paint viscosity, airflow, temperature, and conveyor speed—feeds into the twin. AI analyzes this data and runs simulations to predict how changes in one parameter affect coating uniformity and energy use. Based on the results, the system automatically adjusts robot spray speed, nozzle flow rate, oven temperature, and conveyor speed to optimize coverage, reduce overspray, and minimize energy consumption.

This approach enables adaptive, real-time process optimization, ensuring high-quality finishes under varying conditions while improving throughput and reducing energy costs.

C. Quality Control

Digital twins combined with computer vision and AI enable early detection of defects, reducing scrap rates and improving product quality [24]. In the general assembly area of an automotive plant, precise gap and flush measurements of doors, hoods, and panels are critical for vehicle quality and customer

perception. Variations in panel alignment often originate from upstream processes, such as body line fit or door subassembly installation. By combining digital twins, AI, and computer vision, the factory can detect misalignments early and correlate them to their source.
High-resolution cameras and laser scanners capture gap and flush measurements in real time as doors are installed. The data feeds into a digital twin of the vehicle body, which models all panels and tolerances. AI algorithms analyze the measurements and detect deviations from nominal specifications, identifying patterns that indicate issues originating upstream, such as misaligned body frames or incorrectly positioned hinge assemblies. The system then generates actionable feedback for the body line, allowing operators to correct frame alignment or adjust fixture settings before the next vehicle reaches the general assembly line.
This integrated approach reduces scrap rates, minimizes rework, and ensures consistent vehicle quality. For example, gap and flush deviations can be reduced by 30–50%, while correlated feedback to upstream processes prevents recurring assembly defects, improving overall line efficiency and product fit-and-finish.

D. Real time scheduling and flow control

AI-augmented twins simulate production flows, identify bottlenecks, and optimize scheduling dynamically. This improves lead times and maximizes resource utilization [25]. In an automotive engine manufacturing plant, multiple production lines operate simultaneously, including cylinder machining, assembly, and testing stations. Delays or imbalances in one station can create bottlenecks, leading to longer lead times and underutilized machines. By implementing AI-augmented digital twins, the plant can simulate production flows in real time and dynamically adjust scheduling to optimize throughput.
With AI and Digital twin systems, the system dynamically reallocates resources, adjusts job sequences, and modifies conveyor speeds or batch sizes to prevent bottlenecks. For example, if a cylinder boring station slows down, the twin can prioritize downstream assembly jobs from another line or temporarily reroute parts to an alternate machining cell.
This approach ensures continuous optimization of production flow, improves machine utilization, and shortens lead times. In practice, engine plants using AI-augmented twins have reported a 10–15% increase in throughput, a 20% reduction in machine idle time, and more predictable delivery schedules.

E. Workforce training and augmented operations

Virtual twins combined with AR/VR can train operators on complex systems. AI-generated scenarios prepare staff for rare events and support augmented decision-making [26]. This can be explained by an example of low volume battery assembly line. The operators must handle complex tasks such as high-voltage battery pack assembly, module testing, and safety-critical procedures. Mistakes or delays can compromise quality, safety, and production efficiency. By combining virtual twins with AR/VR and AI, the plant can provide advanced training and operational support.
Each battery assembly workstation has a virtual twin that mirrors the real environment, including tools, components, and process steps. Using AR/VR headsets, operators can interact with the virtual environment to practice assembly procedures, understand component tolerances, and troubleshoot issues without risk to actual hardware. AI generates a wide range of scenarios, including rare or emergency events—such as module misalignment, voltage spikes, or unexpected part defects—allowing staff to train for situations they might rarely encounter on the real line.
During live operations, AR overlays can guide operators in real time, showing step-by-step instructions, highlighting potential errors, and suggesting corrective actions based on the AI's analysis of sensor data and the digital twin. This combination of training and augmented decision-making improves operator skill, reduces human errors, and ensures safety and efficiency in complex processes.

V. BENEFITS

Integrating AI with digital twins in manufacturing provides:

- Increased Equipment Uptime: Predictive maintenance reduces downtime and improves Overall Equipment Effectiveness (OEE) [27].
- Higher Throughput and Efficiency: Real-time optimization and dynamic scheduling reduce idle and blocked times.
- Improved Quality: Early defect detection lowers scrap and rework.
- Reduced Operational Costs: Optimized resource utilization and minimized energy consumption.
- Enhanced Flexibility: Rapid adaptation to product changes, material variability, and demand fluctuations.
- Better Decision-Making: AI insights combined with twin visualization improve situational awareness for operators [28].

VI. CHALLENGES AND CONSIDERATIONS

Despite the advantages, several challenges must be addressed:

A. Data Quality and Readiness

High-quality, accurate and timely data is the foundation of both digital twins and AI models. Incomplete, noisy, or inconsistent sensor data can compromise the fidelity of the twin and reduce the accuracy of AI predictions. Additionally, most of use cases would be driven by correlation of data, there is a possibility of prediction accuracy being lower than expected and findings must be interpreted accordingly. For example, missing vibration data from a robotic arm could lead to undetected mechanical wear, resulting in unplanned downtime. Ensuring proper sensor calibration, data cleansing, and real-time validation is critical to maintaining system reliability [29].

B. Twin model fidelity

Creating an accurate representation of complex machines, production lines, or processes requires detailed modeling of physics, material properties, and operational dynamics. Overly simplified models may fail to capture critical failure modes, while highly detailed models demand continuous calibration to reflect wear, environmental changes, and process variations. For instance, a digital twin of an EV battery assembly line must account for variability in battery module tolerances, thermal behavior, and assembly ergonomics amongst other things, to remain useful [30].

C. AI model lifecycle

AI models are susceptible to concept drift, where the statistical relationships they learned from historical data no longer hold due to changes in operations, equipment, or materials. Without continuous monitoring, retraining, and validation, predictive maintenance or process optimization recommendations may become inaccurate. Establishing robust retraining pipelines and automated performance monitoring is essential for long-term AI reliability.[31].

D. Integration and interoperability

Digital twins must interface seamlessly with existing infrastructure, including legacy PLCs, MES/ERP systems, and SCADA platforms. Differences in protocols, data formats, or update frequencies can hinder real-time synchronization and limit the actionable insights available. Integration requires careful planning, middleware solutions, and possibly upgrading older equipment to support real-time connectivity [32]. Additionally, information security challenges and lack of resourcing can delay the process further.

E. Safety and governance

Automated or AI-driven decisions must incorporate fail-safes, emergency stops, and human oversight to prevent unsafe operations [33]. For example, in robotic assembly or battery handling, an AI recommendation to increase production speed must not compromise operator safety or exceed mechanical limits. Establishing governance frameworks, safety thresholds, and audit trails is critical for regulatory compliance and operational confidence.

F. Scalability and cost

Deploying digital twins with AI capabilities requires significant investment in sensors, edge devices, computational resources, and software development. Scaling from a pilot line to full production can be expensive and complex [34]. Clear business cases, ROI analyses, and phased deployment strategies are necessary to justify costs and ensure measurable value. Additionally, ongoing maintenance, updates, and staff training add to long-term operational expenses.

VII. FUTURE TRENDS

A. Cognitive digital twins

Cognitive digital twins go beyond traditional simulations by integrating graph learning, knowledge graphs, and advanced AI to enable more complex decision-making. These twins can understand relationships between components, processes, and systems, allowing predictive and prescriptive analytics at a higher level. For example, a cognitive twin of an EV assembly line could analyze interactions between battery installation, robotic welding, and paint curing to suggest optimal production adjustments in real time [35].

B. Generative AI for twin design

Generative AI is increasingly being used to automate the creation and optimization of digital twin models. Instead of manually defining physics, parameters, and process rules, AI can generate high-fidelity twin models by learning from historical data, sensor streams, and simulation outcomes. This accelerates deployment, improves accuracy, and enables rapid adaptation to new machinery or product variants [36].

C. Extended reality (XR) Integration

The integration of AR and VR with digital twins allows immersive training, real-time monitoring, and human-in-the-loop operations. Operators can practice assembly, maintenance, or emergency procedures in virtual environments, while managers can visualize production line status in real time. XR also supports remote collaboration, where engineers across locations can interact with the same virtual twin simultaneously.[37].

D. Autonomous Manufacturing

Future manufacturing systems aim to become fully adaptive, with digital twins and AI enabling self-optimizing lines that require minimal human intervention and may result in lights-off factories with minimal oversight. Machines could automatically adjust speeds, sequencing, and maintenance schedules in response to real-time production conditions, improving throughput, reducing waste, and maintaining quality consistently.

E. Edge Analytics

Deploying AI inference and twin simulations at the edge—near the machinery rather than in centralized cloud servers—reduces latency and enables real-time decision-making. For example, predictive maintenance alerts or process optimization recommendations can be delivered instantly, which is critical for high-speed assembly lines or safety-critical operations like battery handling. [38].

F. Factory metaverse

The concept of a factory metaverse involves networked digital twins representing entire factories and extended supply chains. This enables collaborative scenario simulations, production planning, and remote monitoring across multiple sites. Companies can simulate disruptions, optimize logistics, and train staff in a fully virtual yet synchronized representation of the physical ecosystem.[39].

G. Industrial AI- A New age manufacturing ecosystem synergy

The real objective in our view of an Industrial AI platform would be to converge the physical and cognitive abilities that result in enhancement of manufacturing value chain. Fig. 3 elaborates on framework to use Industrial AI ecosystem

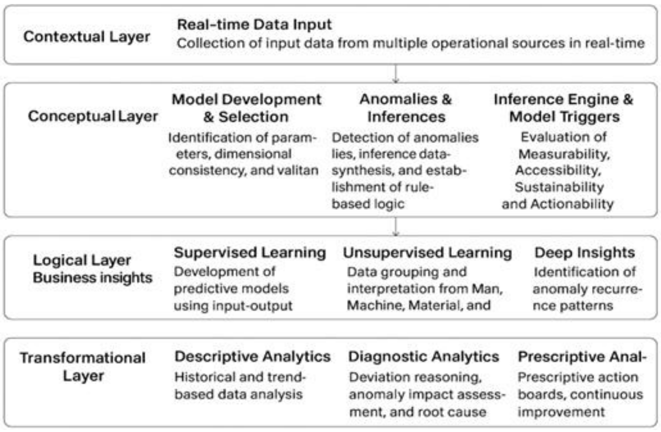

Fig. 3: Framework for new age manufacturing ecosystem

VIII. CONCLUSION

AI-enabled digital twins offer a powerful approach to real-time manufacturing control, bridging the gap between physical operations and intelligent decision-making. Their integration supports predictive maintenance, dynamic process optimization, quality assurance, and adaptive scheduling. While challenges exist in data management, model maintenance, and system integration, a well-structured implementation framework can unlock significant operational benefits. As technology evolves, AI and digital twins will form the foundation of next-generation autonomous, flexible, and resilient smart manufacturing systems.

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