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Artificial Intelligence in Digital Twins for Adaptive Production Planning

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Abstract: ***This study examines the role of artificial intelligence (AI) in digital twins for adaptive production planning under volatile manufacturing conditions. The purpose is to develop a conceptual approach that integrates AI into digital twin architectures to improve planning responsiveness and decision quality. The method combines a focused analytical review of recent literature, conceptual system design, and a hypothetical scenario-based validation logic. The proposed architecture integrates real-time data acquisition, system-state modelling, scenario simulation, predictive analytics, and decision support. The analysis shows that AI strengthens digital twins by enabling bottleneck prediction, disruption detection, scenario evaluation, and maintenance-aware planning adjustments. The paper concludes that integrating AI into digital twins supports a shift from static planning to adaptive, data-driven planning with improved responsiveness and system stability.***

Keywords: artificial intelligence, digital twin, production system, adaptive planning, smart manufacturing, decision support, Industry 4.0, manufacturing systems

1. Introduction

Manufacturing enterprises are increasingly expected to respond to shorter delivery windows, fluctuating order portfolios, higher customization, and stronger cost pressure. In parallel, shop-floor operations are influenced by machine failures, variable processing times, maintenance interventions, workforce constraints, and material availability issues. Planning quality is therefore determined not only by the correctness of the initial schedule but also by the speed and accuracy with which the enterprise revises that schedule when disturbances arise.

Traditional production planning approaches remain useful for establishing baseline schedules; however, they often rely on deterministic assumptions, periodic updates, and limited feedback from the physical system. In dynamic environments, this creates a gap between the planned state and the actual state of the production system. Once this gap widens, previously feasible schedules can generate queue growth, unbalanced workloads, missed due dates, and lower resource utilization.

The digital twin has emerged as an important concept in this context. Rather than functioning as a static digital model, a digital twin maintains a continuously updated virtual representation of the physical production system and can support simulation under current operating conditions. At the same time, the rapid development of AI opens additional opportunities for industrial planning because forecasting, anomaly detection, and decision-support algorithms can transform the twin from a monitoring tool into an active planning instrument.

The objective of this paper is to develop and substantiate an approach to the use of AI within the digital twin of a production system in order to improve the quality and adaptability of production planning in a changing manufacturing environment. The object of research is the production system of an industrial enterprise. The subject of research is the methods and mechanisms for applying AI in the digital twin of a production system for adaptive planning of production processes. The research hypothesis is that integrating AI algorithms into the digital twin of a production system improves adaptive planning by forecasting deviations, evaluating alternative scenarios, and enabling timely schedule correction.

2. Research Method

The study uses a conceptual and analytical research design. Its purpose is not to validate a specific algorithm experimentally, but to derive a coherent architecture for AI-enabled adaptive planning from recent manufacturing-systems research and from the logic of planning, execution, and control in industrial enterprises.

The literature base was selected using three criteria. First, the sources had to address at least one of the following domains: production planning and control, digital twins in manufacturing, AI in manufacturing systems, or the integration of production, maintenance, and quality decisions. Second, priority was given to recent peer-reviewed sources published mainly in 2024 and 2025, complemented by foundational works on digital twins used to clarify core concepts [8], [9]. Third, the selected sources had to contribute either conceptual frameworks, review evidence, or implementation-oriented insights relevant to adaptive planning [1]-[7].

The analytical framework used in the paper compares approaches across five dimensions: representation of the current system state, quality of data integration, scenario-simulation capability, predictive capability, and support for adaptive decision making. On this basis, the paper derives the proposed architecture of an intelligent digital twin and then examines its operational logic through a hypothetical scenario-based validation. The validation does not claim empirical proof; instead, it tests whether the proposed architecture can generate coherent planning responses to representative disturbances such as machine failures, priority changes, and resource shortages.

3. Analysis of Existing Approaches to Planning and Digital Twins

Production planning traditionally includes demand translation, capacity allocation, sequencing, dispatching, and schedule control. In many enterprises, these functions are implemented through ERP, MES, APS, or custom planning routines. Although such systems provide planning discipline, they often remain structurally rigid when the pace of environmental change exceeds the refresh rate of planning cycles. Under such conditions, decision-makers often resort to manual interventions that are difficult to standardize and scale.

Adaptive planning follows a different logic. Instead of assuming that the initial schedule will remain valid until the next formal planning cycle, it treats the schedule as a controllable object that may require frequent revision based on real operational feedback. This makes data latency, model fidelity, and decision support central design variables of the planning system rather than peripheral IT concerns.

The digital twin has become especially important in this context. A digital twin of a production system combines the structural representation of equipment, routing logic, process constraints, and real-time operational data. Unlike a conventional simulation model used only periodically, the digital twin maintains an active link between the physical and virtual spaces. This enables a more accurate representation of the current production state and provides a basis for what-if analysis under actual conditions. Recent studies show that digital twins are increasingly applied to dynamic scheduling, factory planning, and production control [1]-[5]. At the same time, review papers emphasize that their practical value depends on integration with predictive and decision-making capabilities rather than on visualization alone [4]-[7].

A comparison of major planning approaches shows a clear progression from static scheduling toward adaptive control. Traditional planning provides baseline structure but reacts slowly to disturbances. MES-supported planning improves execution visibility, yet it remains strongly rule-driven. Digital twin-based planning adds real-time system representation and scenario simulation, while AI-enabled digital twins extend these capabilities through forecasting, bottleneck prediction, and adaptive decision support.

Despite the growth of interest in AI-enabled digital twins, a practical and methodological gap remains between technological potential and production-planning application. Many studies focus on architecture, data models, or algorithmic methods in isolation. Fewer explain how AI should be embedded into the enterprise planning loop, how scenario evaluation should be structured, and how planning decisions should be adapted on the basis of twin-derived insights. This gap defines the research relevance of the present paper.

4. Problems of Adaptive Planning in Production Systems

Adaptive planning becomes critical when the production environment is characterized by volatility and interdependence. Disturbances in one part of the system often propagate to other parts through queues, shared resources, and precedence constraints. Even a minor deviation in processing time or a short equipment stoppage can trigger missed synchronizations, excessive work-in-process, or underutilization of downstream assets.

Several problem groups can be distinguished. The first group is related to uncertainty of demand and order priorities. Orders may be added, postponed, expedited, or modified after the formal plan has already been released. In such cases, the production system needs to revise priorities without destroying overall flow balance. The second group concerns equipment reliability and technical availability. Unexpected failures and maintenance interruptions distort loading assumptions and reduce effective capacity. The third group includes labor and material constraints, such as temporary workforce shortages or delays in component supply.

A further challenge is the limited observability of the current production state. In many enterprises, data about actual progress, equipment status, and queue accumulation are fragmented across information systems or recorded with delays. As a result, rescheduling decisions are sometimes based on incomplete information. Even when a planner recognizes a deviation, the evaluation of response alternatives often remains intuitive rather than analytically supported.

From a systems perspective, the planning problem is not limited to generating a new sequence of jobs. It also includes preserving feasibility, balancing workloads, minimizing disruption costs, and avoiding local decisions that damage global performance. Therefore, adaptive planning requires an integrated representation of the system, the ability to forecast the likely consequences of disturbances, and a mechanism for selecting the most robust corrective action.

These requirements exceed the capabilities of static planning models. Static models provide a baseline, but they do not inherently support continuous synchronization with shop-floor reality. Consequently, adaptive planning requires a digital infrastructure that captures the actual state of the system and analytical methods that can convert state information into actionable planning recommendations.

5. Concept of Using Artificial Intelligence in the Digital Twin

The proposed concept treats the digital twin as the core analytical layer of adaptive production planning [9]. The twin continuously consolidates data from the physical production environment and forms a virtual representation of system state, including order progress, equipment availability, queue levels, processing capacities, and current resource assignments. On this basis, AI modules perform

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predictive and evaluative functions that support timely plan correction.

The architecture consists of five interacting levels. The first level is the physical level, which includes production equipment, workstations, transport assets, operators, orders, and material flows. The second level is the data acquisition and integration level, where information is collected from ERP, MES, SCADA, IIoT sensors, maintenance systems, and manual operator inputs. The third level is the digital twin level, where the structure, constraints, and current state of the production system are represented in a virtual environment. The fourth level is the AI level, which executes forecasting, anomaly detection, bottleneck identification, state classification, and scenario scoring. The fifth level is the decision layer, where recommendations are transformed into adaptive planning actions such as resequencing, load redistribution, or schedule revision.

A conceptual distinction must be made between the digital model, the digital shadow, and the digital twin [8]. A digital model may represent the production system structurally but without automatic data exchange. A digital shadow includes one-way data transfer from the physical system to the model. A digital twin establishes a tighter and more dynamic connection between the physical and virtual domains, enabling continuous state update, simulation, and potentially bidirectional control logic. For adaptive planning, this distinction is essential because the effectiveness of replanning depends on the timeliness and fidelity of state synchronization.

The scientific contribution of the proposed approach lies in combining real-time system-state representation, predictive AI models, and scenario-based plan correction within a single conceptual planning loop. In this logic, AI is not treated as a standalone analytical tool. Instead, it is embedded into the digital twin as a functional mechanism that transforms state information into adaptive planning actions.

6. Use of the Intelligent Digital Twin for Adaptive Planning

The intelligent digital twin supports adaptive planning through several practical functions. First, it enables dynamic workload assessment by monitoring operation execution, queue lengths, equipment states, and order-release patterns. AI models can forecast whether a given resource is likely to become a bottleneck within a specified planning horizon, allowing planners to intervene before the bottleneck fully materializes.

Second, it supports disruption-aware rescheduling. When a machine failure, quality issue, maintenance stop, or labor shortage occurs, the digital twin can generate a current-state snapshot and simulate alternative planning responses. AI can rank these alternatives against explicit criteria such as due-date adherence, throughput, changeover costs, and resource utilization. Third, the twin supports adaptive order prioritization in make-to-order and mixed-model environments by identifying release sequences and routing states that are likely to create congestion or service failures. Fourth, the architecture enables capacity-sensitive plan revision by comparing planned capacity with actual effective capacity under disturbances, reduced performance, or maintenance constraints. Fifth, it supports learning from previous disturbances. Historical data on the disturbance type, corrective action, and resulting performance can be used to refine future recommendations. In this way, adaptive planning becomes not only reactive but progressively self-improving.

Table 2: Hypothetical scenario-based validation of the proposed architecture

Scenario	AI-enabled twin response	Expected planning effect
Urgent high-priority order enters the system	Twin updates WIP and capacity state; AI evaluates alternative resequencing options	Improved due-date protection with controlled disruption of existing jobs
Unexpected machine breakdown on a constrained resource	Twin simulates rerouting and load redistribution; AI ranks feasible recovery scenarios	Reduced queue escalation and faster recovery of schedule feasibility
Temporary operator shortage on one shift	Twin recalculates effective capacity; AI recommends revised release rate and priority rules	More balanced loading and lower risk of downstream starvation or overload

Table 2 provides a structured validation logic for the proposed concept. Although the scenarios are hypothetical, they demonstrate that the architecture produces coherent adaptive-planning responses by combining real-time state representation, simulation of alternatives, and AI-based evaluation of corrective actions. Figure 1 summarizes the conceptual architecture of the intelligent digital twin for adaptive planning.

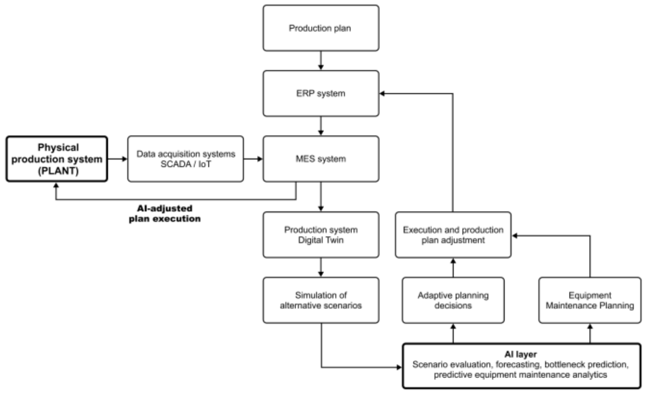

Figure 1: Conceptual architecture of AI-enabled adaptive planning based on a production system digital twin

Figure 1 illustrates the proposed architecture for adaptive production planning based on the integration of a production system digital twin and an AI analytics layer. The physical production system generates real-time operational data collected through SCADA/IoT-based data acquisition systems and transferred to the MES environment, where execution-related information is combined with the production plan received from the ERP system. These data update the digital twin, which provides the basis for simulating alternative production scenarios. The AI layer evaluates the simulated scenarios, performs forecasting, identifies potential bottlenecks, and supports predictive equipment maintenance analytics. Based on these outputs, adaptive planning decisions are generated and translated into production-plan adjustments that are fed back into the ERP/MES planning and execution loop.

7. Expected Effects and Implementation Limitations

The practical significance of the proposed approach lies in its potential to improve both planning quality and production resilience. If implemented correctly, the intelligent digital twin can reduce the time required to recognize a deviation, evaluate alternatives, and issue an updated plan. This improves responsiveness and lowers the probability that local disturbances will escalate into system-wide performance losses.

Expected operational effects include higher schedule feasibility, lower equipment idle time, lower queue accumulation, more balanced loading of constrained resources, and better adherence to promised delivery dates. From a managerial perspective, the approach also increases the transparency of decision making by linking corrective actions to explicit state data and scenario-evaluation criteria. Recent manufacturing research increasingly emphasizes that production, maintenance, and quality should not be optimized independently because these domains interact strongly in practice [6], [7]. By serving as a common analytical layer, the digital twin can help coordinate decisions that would otherwise remain siloed.

At the same time, implementation limitations should be recognized. The first limitation concerns data quality and interoperability. Adaptive planning requires timely, structured, and consistent data from multiple systems, which is often difficult to achieve in legacy environments. The second limitation concerns model validity. If the digital twin poorly represents routing logic, capacities, or stochastic behavior, then AI-driven recommendations may appear analytically sophisticated while remaining operationally misleading.

The third limitation concerns organizational readiness. Even technically sound planning recommendations may not be accepted if planners and production managers do not trust the system, do not understand the recommendation logic, or cannot embed it into existing decision rights. A fourth limitation is the need to avoid black-box dependence in high-impact planning decisions. In many industrial contexts, planners require interpretable support rather than opaque automation. Consequently, the intelligent digital twin should be implemented as a decision-support mechanism with staged deployment, measurable validation criteria, and explicit human oversight.

8. Conclusion

This study analyzed the integration of artificial intelligence into digital twins for adaptive production planning. The results show that digital twins provide real-time system representation, while AI enables prediction, scenario evaluation, and decision support. The proposed architecture demonstrates how these elements can be combined into a continuous planning loop.

The findings confirm, at a conceptual level, that AI-enhanced digital twins improve responsiveness and planning robustness in dynamic manufacturing environments. The main contribution of the paper is the formalization of an architecture that links planning data, execution data, simulation, predictive analytics, and maintenance-aware decision support within a single adaptive-planning contour.

Future work should focus on empirical validation, performance metrics for AI-driven adaptive planning, and improved model interpretability for practical industrial implementation.

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