Universal Library of Engineering Technology | Research Article

ISSN: 3064-996X | Volume 3, Issue 3

Open Access | PP: 48-53

DOI: https://doi.org/10.70315/uloap.ulete.2026.0303008

A Conceptual Framework for AI-Enabled Digital Twin-Based Production Planning

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Abstract

Modern production systems operate under conditions of demand volatility, resource constraints, equipment disturbances, and changing operational priorities. Under such conditions, conventional planning methods based on static assumptions are often unable to maintain schedule feasibility and system stability. This paper examines the use of artificial intelligence (AI) within the architecture of a digital twin of a production system to support adaptive planning. The study systematizes the limitations of traditional production planning, clarifies the functional role of the digital twin as a dynamic representation of the physical production system, and demonstrates how AI extends that role from passive monitoring to predictive and prescriptive decision support. A conceptual architecture of an intelligent digital twin is proposed, integrating operational data acquisition, state modelling, forecasting, scenario evaluation, and plan correction mechanisms. Particular attention is given to the use of AI for bottleneck prediction, disruption detection, workload balancing, equipment downtime risk assessment, and the generation of recommendations for schedule adjustment. Practical application scenarios are discussed for order priority changes, equipment failures, productivity deviations, and resource shortages. The paper concludes that embedding AI into the digital twin enables a transition from static planning to an adaptive planning model based on continuous situational awareness and scenario-driven decision making.

Keywords: *Artificial Intelligence, Digital Twin, Production System, Adaptive Planning, Smart Manufacturing, Decision Support, Industry 4.0, Manufacturing Systems.*

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. As a result, planning quality is determined not only by the correctness of the initial plan but also by the speed and accuracy with which the enterprise can revise that plan 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 concept of the digital twin has become one of the most promising instruments for reducing this gap. A digital twin is not merely a static digital model; it is a continuously updated virtual representation of the physical system, linked to operational data and capable of reflecting the current state and logic of production processes. When coupled with simulation and analytics, the digital twin can be used not only for visualization but also for experimentation with alternative operating scenarios. At the same time, the rapid progress of AI opens additional opportunities for the industrial use of digital twins. Forecasting models, anomaly detection methods, and decision-support algorithms can transform a digital twin into an active planning instrument. This shift is particularly relevant for adaptive planning, where schedules and resource allocations must be revised in response to current conditions and expected future deviations.

Citation: Dmitrii Voistrochenko, "A Conceptual Framework for AI-Enabled Digital Twin-Based Production Planning", Universal Library of Engineering Technology, 2026; 3(3): 48-53. DOI: https://doi.org/10.70315/uloap.ulete.2026.0303008.

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.

MATERIALS AND METHODS

This study uses a conceptual research design combining literature analysis, comparative analysis, and architectural synthesis. The source base consists of the nine publications cited in the paper. It includes recent studies on digital twin-based production planning and scheduling, factory planning, AI-enabled digital twins, and integration of production, maintenance, and quality functions, together with foundational works describing the digital twin concept and its application in smart manufacturing. The sources were used to identify common limitations of conventional planning and recurring functional capabilities associated with digital twins and AI. The study does not claim a systematic literature review; rather, the literature provides the analytical basis for development of the proposed conceptual architecture.

The research procedure consisted of three stages. First, planning approaches were compared according to capabilities relevant to adaptive production control, including real-time state representation, responsiveness to disturbances, predictive capability, scenario evaluation, and support for rescheduling. This comparison forms the basis for Table 1. Second, operational disturbances that create the need for adaptive planning were analyzed, including changes in order priorities, equipment failures, productivity deviations, labor constraints, and material shortages. Their implications were considered in terms of schedule feasibility, resource loading, queue formation, and delivery performance.

Third, a conceptual architecture was developed by synthesizing these functional requirements into interconnected layers: the physical production system, data acquisition and integration, the digital twin, AI analytics, and decision support. The proposed architecture was then examined through scenario-based reasoning for bottleneck prediction, disruption-aware rescheduling, order reprioritization, capacity-sensitive plan revision, and learning from previous disturbances. The analysis is conceptual and does not include experimental validation in a specific factory; therefore, the resulting architecture and expected effects are interpreted as a framework for subsequent empirical implementation and validation.

RESULTS

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 may 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, which are difficult to standardize and scale. Adaptive planning requires a different logic. Instead of assuming that the initial schedule will remain valid until the next formal planning cycle, it assumes that the schedule is a controllable object that may need 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 emerged as an important concept in this context. A digital twin of a production system typically combines the structural representation of equipment, routing logic, process constraints, and real-time operational data. Unlike a conventional simulation model that may be used only periodically, the digital twin maintains an active link between the physical and virtual spaces. This enables a more accurate representation of the production system state and provides a basis for what-if analysis under current conditions. Recent studies indicate that digital twins are increasingly applied to production planning and control, dynamic scheduling, and factory planning. They are used to improve visibility, support scenario analysis, and increase responsiveness under demand variability [1], [2], [3]. At the same time, review papers emphasize that the real value of digital twins depends on their integration with predictive and decision-making capabilities rather than on visualization alone [4], [5]. This is where AI becomes particularly significant. In manufacturing environments, AI can support forecasting, anomaly detection, classification of system states, optimization of decision alternatives, and intelligent recommendation generation. When integrated with the digital twin, AI allows the virtual model to anticipate future system behavior instead of merely describing the current one. In other words, the digital twin becomes capable of moving from descriptive representation to predictive and prescriptive support.

To systematize the evolution of production planning approaches in manufacturing systems, Table 1 presents a comparative analysis of traditional planning, MES-supported planning, digital twin-based planning, and AI-enabled digital twin approaches. The comparison highlights that the integration of AI with digital twins extends production planning from static or reactive control toward predictive and adaptive decision-making.

Table 1. Comparative analysis of planning approaches in manufacturing systems

Approach	*Key capabilities*	*Main limitations*
Traditional production planning	Based on predefined schedules and periodic updates; suitable for stable production conditions	Low adaptability, delayed response to disturbances, limited support for dynamic rescheduling
MES-supported planning	Uses execution data and dispatching rules for operational control; improves visibility of shop-floor status	Limited predictive capability; strong dependence on preset rules
Digital twin-based planning	Provides real-time system representation and supports simulation of alternative production scenarios	Limited intelligence for automated scenario evaluation and predictive decision support
AI-enabled digital twin for adaptive planning	Combines real-time system representation, scenario simulation, forecasting, bottleneck prediction, and adaptive decision support	High requirements for data quality, system integration, and implementation effort

As shown in Table 1, traditional and rule-based planning approaches provide only limited adaptability in dynamic production environments. Digital twin-based planning significantly improves visibility and scenario modelling; however, its predictive and decision-support capabilities remain restricted without the integration of AI methods. This creates the basis for the proposed AI-enabled digital twin approach for adaptive production planning.

However, despite the growth of interest in AI-enabled digital twins, there is still a practical and methodological gap between technological potential and production planning application. Many studies focus on architecture, data models, or algorithmic methods in isolation. Fewer works explain how AI should be embedded into the planning loop of the enterprise, 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.

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 the planner recognizes a deviation, the evaluation of response alternatives may remain 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 generally assume fixed routing, nominal processing times, and periodic schedule revision. They provide a baseline, but they do not inherently contain mechanisms for continuous synchronization with shop-floor reality. Consequently, adaptive planning must be supported by a digital infrastructure that captures the actual state of the system and by analytical methods that can convert state information into actionable planning recommendations.

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 [8]. 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 predictive and evaluative functions that support timely plan correction.

The architecture may be represented by 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. The central role of AI in this architecture is not to replace the planner but to increase the intelligence of the planning loop. Forecasting models can estimate near-term queue growth, equipment downtime probability, or processing-time deviations based on historical and real-time data. Classification and anomaly detection methods can reveal unstable conditions before they become operational failures. Optimization-oriented AI methods can evaluate alternative schedule corrections according to selected performance criteria, such as due-date adherence, throughput, changeover costs, and resource utilization.

A conceptual distinction should be made between the digital model, the digital shadow, and the digital twin [9]. 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 includes 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 novelty 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 contour. In this logic, AI is not treated as a standalone analytical tool; rather, it is embedded into the digital twin as a functional mechanism that transforms state information into adaptive planning actions. This integrated use of current data, predictive inference, and scenario correction provides the basis for a more resilient planning system.

Use of the Intelligent Digital Twin for Adaptive Planning

The intelligent digital twin can support adaptive planning through several practical functions. The first function is dynamic workload assessment. By continuously monitoring the execution of operations, queue lengths, equipment states, and order release patterns, the twin can identify emerging overload conditions. AI models can then forecast whether a given resource is likely to become a bottleneck within a specified planning horizon. This allows planners to intervene before the bottleneck fully materializes.

The second function is 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 using multi-criteria evaluation. For example, one response may minimize tardiness but increase changeover losses, while another may preserve flow stability with a moderate due-date penalty. The value of AI in this context is the speed and consistency of evaluating such trade-offs under time pressure.

The third function is adaptive prioritization of orders. In make-to-order and mixed-model environments, priority rules cannot remain constant under all circumstances. AI models embedded in the digital twin can identify order combinations and routing states that are likely to create congestion or service failures. On that basis, the system can recommend changes in release sequence, resource assignment, or job splitting. Such recommendations do not eliminate managerial judgment; rather, they make it more evidence-based.

The fourth function is capacity-sensitive plan revision. The digital twin allows the planner to compare planned capacity and actual effective capacity, which may be altered by disturbances, reduced performance, or maintenance. AI can estimate the expected performance envelope of each resource and support decisions on whether to reroute work, extend shifts, defer low-priority orders, or rebalance the load across parallel resources.

The fifth function is learning from previous disturbances. Unlike purely rule-based rescheduling, the proposed concept allows the system to accumulate experience from prior planning corrections. Historical data about the type of disturbance, implemented corrective action, and resulting performance can be used to retrain models and improve future recommendations. In this way, adaptive planning becomes not only reactive but progressively self-improving.

Figure 1 summarizes the conceptual architecture of the intelligent digital twin for adaptive planning.

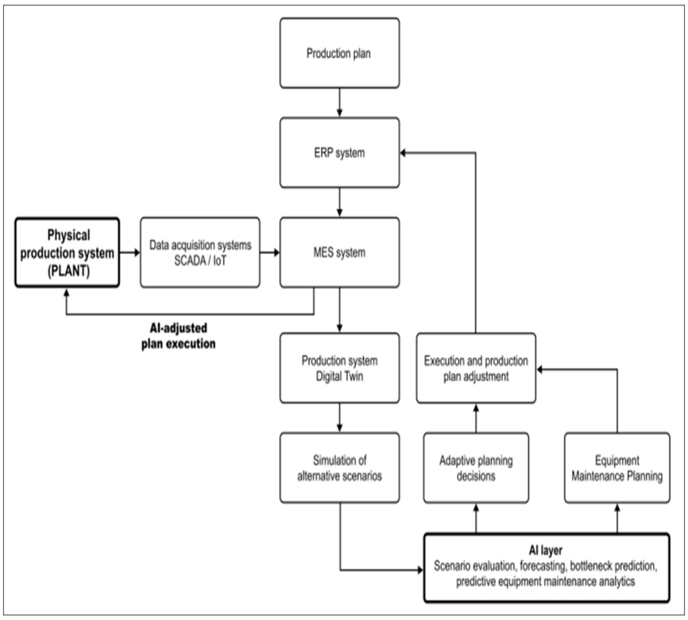

Figure 1. Conceptual architecture of AI-enabled adaptive planning based on a production system digital twin

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 are used to update the digital twin of the production system, which serves as 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 execution and production plan adjustments, which are fed back into the ERP/MES planning and execution loop. This closed-loop architecture enables continuous synchronization between planning, execution, and the actual state of the production system.

DISCUSSION

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 transparency of decision making by linking corrective actions to explicit state data and scenario evaluation criteria. In other words, planning becomes more explainable and less dependent on ad hoc reactions. The concept may also support integration across production, maintenance, and quality functions. Recent manufacturing research increasingly emphasizes that these domains should not be optimized independently, because production sequencing, equipment reliability, and quality performance 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. Therefore, successful implementation requires not only architecture development but also governance, validation procedures, and human-centered interface design. The fourth limitation is the need to avoid black-box dependence in high-impact planning decisions. In many industrial contexts, planners require interpretable support, not 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. Such an approach is more realistic for industrial enterprises than the immediate pursuit of fully autonomous planning.

CONCLUSION

This paper has examined the use of AI in the digital twin of a production system for adaptive planning. The analysis has shown that traditional planning methods, while still necessary for baseline schedule formation, are often insufficient under volatile operating conditions because they do not provide continuous synchronization between the planned and actual states of the production system.

The digital twin provides the structural and informational foundation for this synchronization by creating a continuously updated virtual representation of the physical system. AI extends this foundation by enabling prediction of deviations, identification of bottlenecks, evaluation of corrective scenarios, and generation of recommendations for schedule adaptation. On this basis, the paper proposed a conceptual architecture of an intelligent digital twin that integrates physical resources, data acquisition, virtual state modelling, predictive analytics, and decision support.

The research hypothesis is therefore supported at the conceptual level: embedding AI into the digital twin makes it possible to move from static planning toward an adaptive planning model based on continuous situational awareness, scenario analysis, and timely plan correction. The practical significance of the approach lies in its potential to improve schedule robustness, responsiveness to disturbances, and the overall stability of manufacturing operations.

Further research may focus on the formalization of performance indicators for AI-driven adaptive planning, validation of the proposed architecture in specific industrial environments, and development of methods for balancing predictive accuracy with model interpretability in operational decision support.

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