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An AI–Digital Twin Approach to Closed-Loop Risk-Aware Resource Orchestration

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ABSTRACT

Dynamic resource systems must respond to changing operating conditions, uncertain disturbances, and competing performance requirements. Static allocation and prediction-only strategies may fail to incorporate the risk implications of future system states into repeated resource decisions. This study develops an AI-Digital Twin approach to closed-loop risk-aware resource orchestration. The approach uses observation-based twin synchronization, a supervised multilayer perceptron for future-state prediction, an action-dependent risk operator, and a constrained utility-cost-risk objective to select resource actions over successive decision cycles. After each action is executed, the resulting system observation is used to update the twin state and inform the next decision. The approach is evaluated in a simulation comprising 120 decision cycles, four strategies, and 12 independent random seeds per strategy: static allocation, predictive allocation, risk-aware orchestration, and the proposed closed-loop strategy. Performance is assessed using utility, deployment cost, shortage, volatility, constraint violation, and composite risk. The proposed strategy achieves the highest mean utility and the lowest mean shortage, constraint violation, and composite risk among the four strategies. Relative to risk-aware orchestration, it improves utility by 2.34%, reduces shortage by 2.04%, constraint violation by 3.69%, and composite risk by 2.39%, while increasing deployment cost by 5.52%. The difference in volatility is not statistically significant. These results indicate that synchronized prediction, action-dependent risk evaluation, and feedback updating can improve selected risk-sensitive performance dimensions, although the improvement involves a measurable cost trade-off.

1.Introduction

Modern complex systems increasingly depend on tightly coupled interactions among physical assets, digital infrastructures, computational resources, decision processes, and organizational constraints. Such systems are characterized by heterogeneous components, dynamic interdependencies, uncertain operating conditions, and the possibility that local disturbances may propagate across interconnected subsystems. Network research has shown that system topology influences collective behavior, connectivity, and disturbance propagation[1,2]. In highly interconnected systems, these interdependencies may generate systemic effects in which the degradation of one component affects the stability of other components through direct and indirect transmission channels[3–9]. Consequently, effective management of complex systems requires more than isolated component-level optimization. It requires mechanisms that can represent system-wide conditions, anticipate future changes, assess risk, and coordinate resources across interacting entities.

Traditional resource management approaches commonly rely on periodic monitoring, predefined rules, or static optimization. These approaches may be effective under relatively stable conditions but become less suitable when system states change rapidly, resources are constrained, or multiple risks emerge simultaneously. An allocation that is efficient under current conditions may become undesirable when future demand, resource availability, failure probability, or system interactions change. Resource orchestration in complex systems should therefore be treated as a dynamic decision problem involving state awareness, future-state prediction, risk assessment, constraint handling, and continuous adaptation.

Cyber–physical systems (CPSs) provide an important technological foundation for this type of decision support by

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integrating physical processes with sensing, communication, computation, and control[10]. Within this context, digital twins (DTs) have emerged as digital representations of physical systems that support monitoring, simulation, analysis, and decision-making. Existing studies have examined digital twins in terms of their definitions, classifications, architectures, enabling technologies, and modeling perspectives[11–16]. Compared with isolated monitoring tools, digital twins can integrate heterogeneous data, operational states, system relationships, and analytical models within a shared virtual environment.

However, a digital representation alone does not necessarily produce intelligent or adaptive decisions. To support proactive management, a digital twin must be coupled with analytical mechanisms capable of interpreting current conditions, predicting future states, and evaluating alternative actions. The integration of artificial intelligence with digital twins has consequently attracted increasing attention. AI-driven digital twins can support prediction, anomaly detection, intelligent analysis, and adaptive decision support in complex industrial environments[17]. This integration creates the possibility of moving from descriptive monitoring toward predictive and prescriptive system management.

Resource allocation and orchestration represent important applications of this direction. Existing studies have applied digital twins to resource optimization in shared manufacturing, production logistics, and network-oriented environments[18–20]. These studies demonstrate that digital twins can improve resource visibility and support dynamic allocation. Nevertheless, many existing approaches are designed for specific application contexts and primarily emphasize objectives such as utilization, latency, throughput, computational efficiency, or allocation cost. Their decision processes do not always explicitly connect future-state prediction with dynamic risk assessment and subsequent resource orchestration.

This limitation is particularly important in systems where resource decisions must account for both immediate performance and future disruption. The most efficient allocation in terms of short-term utility may not be the safest allocation. Assigning additional resources to a highly utilized component may improve immediate throughput while increasing exposure to overload, instability, or cascading failure. Similarly, minimizing current cost may create greater future shortage or volatility. Therefore, resource orchestration should jointly consider expected utility, operational cost, risk exposure, resource shortage, system volatility, and constraint violation.

The distinction between prediction and risk assessment is central to this problem. Prediction estimates possible future system conditions, whereas risk assessment evaluates the likelihood, severity, and operational consequences associated with those conditions. A predictive model may identify a potential overload, demand surge, or resource imbalance, but this information becomes operationally useful only when it is translated into an appropriate decision response. Accordingly, the key challenge is not merely to improve prediction accuracy, but to establish a clear mechanism through which predicted future conditions and their associated risks influence resource orchestration.

Digital twins may also serve as computational environments for adaptive decision-making. Research on reinforcement twinning has examined the relationship between digital twins and model-based reinforcement learning, illustrating how digital representations can support action evaluation and decision processes[21]. Nevertheless, learning or optimization alone does not resolve the problem of how predicted risk should influence resource orchestration. A system may generate accurate forecasts without incorporating risk into allocation decisions, while an optimization procedure may produce feasible allocations without adequately accounting for changes in future system conditions.

In addition, the credibility and reliability of digital twin outputs must be considered when these outputs support operational decisions. Prediction and simulation results depend on data quality, model assumptions, synchronization accuracy, validation procedures, and uncertainty. Shao et al.[22] emphasize the importance of credibility considerations for digital twins in manufacturing. This implies that a risk-aware orchestration mechanism should not treat predicted states as unquestionable facts. Instead, prediction, risk assessment, decision generation, and feedback updating should be connected so that decisions can be revised as new observations become available.

To address these issues, this study proposes an AI–Digital Twin framework for closed-loop, risk-aware resource orchestration in complex systems. The proposed decision chain is defined as:

System State → Digital Twin Synchronization → Future-State Prediction → Dynamic Risk Assessment → Resource Orchestration → System Response → Feedback Updating

The central mechanism is the use of dynamic risk assessment as the transition between future-state prediction and resource orchestration. In this approach, the digital twin maintains a synchronized representation of the system, AI-based predictive mechanisms estimate possible future conditions, and the risk assessment module evaluates the operational implications of those conditions. The resulting risk information is then incorporated into resource orchestration decisions. After implementation, the system response is observed and used to update the digital twin and subsequent decisions.

The proposed approach differs from conventional digital-twin-based optimization and predictive resource allocation in three respects. First, it explicitly separates future-state prediction from risk assessment and uses risk assessment as a decision-transition mechanism. Second, it evaluates orchestration decisions across multiple dimensions, including utility, cost, risk, shortage, volatility, and constraint violation, rather than relying on a single efficiency objective. Third, it adopts a closed-loop structure in which system responses are fed back into the digital twin for continuous updating and decision revision.

The evaluation is designed to compare three decision regimes:

(1). Static allocation, which applies predefined or non-adaptive resource assignments;

(2). Predictive allocation, which uses predicted system conditions but does not explicitly incorporate dynamic risk adjustment;

(3). Risk-aware orchestration, which integrates future-state prediction, dynamic risk assessment, resource allocation, and feedback updating.

The three approaches are evaluated using utility, cost, risk, shortage, volatility, and constraint violation as the principal performance dimensions.

The main contributions of this study are summarized as follows:

(1). A closed-loop AI–Digital Twin architecture is developed to connect system-state monitoring, digital twin synchronization, future-state prediction, dynamic risk assessment, resource orchestration, system response, and feedback updating within a unified process.

(2). A predictive risk transition mechanism is established to connect future-state intelligence with resource orchestration. This mechanism translates predicted system conditions into risk-sensitive decision information rather than treating prediction as an isolated analytical output.

(3). A multi-dimensional orchestration perspective is formulated by jointly considering utility, cost, risk, shortage, volatility, and constraint violation.

(4). A comparative simulation-based evaluation is designed to assess the proposed approach against static allocation and predictive allocation baselines, while also examining the role of feedback updating and operational governance.

The remainder of this paper is organized as follows. Section 2 reviews related research on complex-system risk, digital twins, AI-driven digital twins, and digital-twin-based resource allocation. Section 3 presents the proposed AI–Digital Twin architecture and closed-loop orchestration process. Section 4 formulates the system state, future-state prediction, dynamic risk assessment, and resource orchestration mechanisms. Section 5 describes the simulation design, baseline methods, evaluation indicators, and experimental settings. Section 6 presents and discusses the simulation results. Section 7 discusses governance, applicability, limitations, and future research directions. Section 8 concludes the study.

2.Related work

2.1.Complex-system interdependencies and risk

Complex systems consist of heterogeneous components whose interactions may produce collective behavior that cannot be adequately explained through isolated component-level analysis. Their operational performance is influenced not only by the condition of individual entities but also by the structure of interdependencies, the distribution of resources, and the propagation of disturbances across connected subsystems. Network-based studies have demonstrated that connectivity and structural organization play an important role in determining system behavior and the transmission of disturbances[1,2].

In interconnected systems, local disruptions may generate consequences beyond the initially affected component. The extent of such consequences depends on the relationships among entities, the direction and strength of dependencies, and the availability of alternative resources or recovery mechanisms. In the context of financial networks, Eisenberg and Noe[3] showed how obligations among interconnected institutions can transmit the effects of payment shortfalls throughout a system. Subsequent studies have examined systemic risk, financial contagion, network vulnerability, and the relationship between interconnectedness and system stability[4–9].

Although these studies primarily address financial and economic networks, their implications are applicable to complex-system management more broadly. In particular, they establish three relevant observations. First, system risk is often generated by interactions rather than by isolated component conditions. Second, the consequences of a disturbance depend on the structure of the surrounding system. Third, decisions that improve the condition of one component may not necessarily improve overall system stability.

These observations are directly relevant to resource management in dynamic environments. When resources are limited, allocation decisions may alter the exposure of different components and affect the propagation of future disturbances. Consequently, resource management should consider not only current utilization and immediate performance but also the potential consequences of resource decisions under changing system conditions.

Conventional risk-management approaches generally focus on identifying hazards, estimating the probability of adverse events, or evaluating the consequences of specified scenarios. Such approaches remain useful for system analysis, but they may be insufficient when system states, resource requirements, and interdependencies evolve continuously. In these circumstances, risk cannot be treated as a fixed characteristic of a component. It is influenced by the current state of the system, anticipated future conditions, resource constraints, and the actions taken during operation.

This perspective motivates the integration of state monitoring, future-state prediction, risk assessment, and resource decision-making. For complex systems, risk assessment should therefore be connected to operational decisions rather than treated solely as an independent analytical output.

2.2.Cyber–physical systems and digital twins

Cyber–physical systems integrate physical processes with sensing, communication, computation, and control, thereby enabling continuous interaction between physical operations and digital decision processes[10]. Through this integration, information collected from physical entities can be processed, analyzed, and used to support monitoring, control, and operational improvement.

Digital twins have developed within this technological context as digital representations of physical objects, processes, or systems that maintain a connection with their physical counterparts. Depending on the application, a digital twin may incorporate real-time data, historical records, mathematical models, simulation capabilities, system relationships, and analytical tools. Its purpose is not limited to representing the physical system but also includes supporting analysis and decision-making throughout the system lifecycle.

The literature has examined digital twins from several complementary perspectives, including their definitions, characteristics, architectures, enabling technologies, and design implications[11–16]. These studies indicate that digital twins are not defined by a single modeling technique. Rather, they represent an integrated technological concept involving data exchange, model representation, synchronization, analysis, and interaction between physical and digital entities.

Several functions are commonly associated with digital-twin implementations. These include the representation of system states, synchronization with physical observations, monitoring and diagnosis, simulation of alternative conditions, prediction of future behavior, and support for operational decisions. The combination of these functions allows a digital twin to serve as an analytical environment rather than merely a visualization or monitoring interface.

The effectiveness of a digital twin depends on the quality of its connection to the physical system and the reliability of the models and data used within it. Data incompleteness, synchronization delays, interoperability limitations, model uncertainty, and implementation complexity may affect the accuracy and usefulness of digital-twin outputs[11–16]. A digital representation may therefore provide substantial information without necessarily producing effective operational decisions.

This distinction is important for resource orchestration. A digital twin can describe the current distribution of resources and system conditions, but additional predictive and decision-oriented mechanisms are required to determine how resources should be adjusted in response to future changes. Digital twins consequently provide an important foundation for adaptive management, while their operational value depends on the analytical and decision mechanisms connected to them.

2.3.AI-enabled digital twins

The integration of artificial intelligence with digital twins has expanded the analytical capabilities of digital-twin environments. Machine-learning and data-driven methods can support pattern recognition, anomaly detection, state estimation, demand forecasting, condition prediction, and decision support. These capabilities enable digital twins to move beyond descriptive monitoring toward predictive and, in some cases, prescriptive applications.

AI-enabled digital twins may be used to estimate future system conditions, identify deviations from expected behavior, and evaluate possible operational responses. Predictive models can be applied to equipment conditions, production demand, workload, resource availability, energy consumption, or other variables relevant to system operation. Learning-based methods may also approximate complex relationships that are difficult to capture through conventional analytical models.

Existing studies have emphasized the role of AI and data-driven technologies in enhancing the analytical functions of digital twins. The integration of machine learning, data processing, and digital representations can improve forecasting and monitoring capabilities, while also creating new challenges related to data quality, interoperability, model transparency, security, and performance evaluation[12-16]. These challenges become more consequential when digital-twin outputs are used to support operational decisions.

Prediction, however, should not be equated with decision-making. A predictive model estimates possible future conditions, whereas a decision mechanism determines how the system should respond to those conditions. For instance, a model may predict a future increase in demand or a possible overload, but the prediction alone does not determine whether resources should be redistributed, whether a particular component should receive priority, or how much operational risk should be accepted.

The distinction is especially relevant to risk-sensitive resource management. A future condition may have different operational implications depending on its probability, severity, exposure, and relationship to other system components. Consequently, predictive information must be interpreted before it can be translated into resource decisions. A prediction that is accurate in statistical terms may still be insufficient for decision-making if its operational consequences are not evaluated.

The reliability of AI-enabled digital twins also requires attention. Digital-twin outputs may be affected by measurement errors, incomplete observations, model mismatch, synchronization inaccuracies, and changes in the underlying system. Lin et al.[15] examined uncertainty-related issues in digital-twin-based management and control environments, highlighting the importance of considering uncertainty when digital-twin outputs support autonomous or semi-autonomous decisions. Shao et al.[22] similarly emphasized credibility considerations for digital twins in manufacturing.

These studies suggest that AI-enabled digital twins should not be treated as isolated prediction systems. Their outputs need to be assessed within an operational process that connects prediction, risk interpretation, decision generation, system response, and subsequent updating.

2.4.Digital-twin-based resource allocation and orchestration

Resource allocation concerns the assignment of limited resources to competing tasks, components, or operational requirements. Depending on the application domain, resources may include production capacity, computing resources, labor, energy, inventory, transportation capacity, communication bandwidth, or emergency supplies. In complex systems, allocation decisions are often affected by changing demand, resource constraints, system dependencies, and competing performance objectives.

Digital twins can support resource allocation by providing an updated representation of system conditions and enabling the evaluation of alternative decisions. Through a digital-twin environment, decision-makers may examine resource utilization, identify bottlenecks, simulate possible allocations, and estimate the consequences of alternative actions before implementing them in the physical system.

Existing studies have applied digital twins to resource-management problems in manufacturing, production logistics, and edge-computing environments. Wang et al.[18] examined a digital-twin-driven service model and the allocation of manufacturing resources in shared manufacturing. Zhao et

al.[19] investigated a digital-twin-enabled dynamic spatial–temporal knowledge graph for production-logistics resource allocation. Han et al.[20] studied digital-twin-assisted resource allocation in edge-computing environments. Collectively, these studies demonstrate the potential of digital twins to improve resource visibility, support dynamic allocation, and coordinate decisions in application-specific settings.

Nevertheless, the objectives of existing resource-allocation studies are often defined primarily in terms of efficiency, utilization, latency, throughput, energy consumption, or cost. These objectives are important for operational performance, but they may not fully capture the consequences of allocation decisions under uncertain and evolving conditions. In particular, an allocation that improves short-term efficiency may increase overload exposure, future shortage, system volatility, or the likelihood of constraint violation.

A distinction can also be made between resource allocation and resource orchestration. Resource allocation generally refers to the assignment of resources at a particular decision point. Resource orchestration has a broader temporal and systemic meaning. It involves the coordinated adjustment, redistribution, prioritization, and management of resources across interacting components as system conditions change. Orchestration may therefore include repeated allocation, constraint handling, priority adjustment, conflict resolution, and feedback-based revision.

For complex systems, resource orchestration cannot be adequately characterized as a one-time optimization problem. It is a dynamic decision process in which current system conditions, predicted future states, risk exposure, operational objectives, and resource constraints must be considered together. This creates a need for decision mechanisms that extend beyond the direct optimization of current resource utilization.

2.5.Risk-aware decision-making in digital-twin environments

Risk-aware decision-making incorporates the possibility and consequences of adverse outcomes into operational decisions. Within a digital-twin environment, risk assessment can draw upon real-time observations, historical data, predictive models, simulation results, and information concerning system interdependencies.

Risk assessment performs a function that is distinct from prediction. Prediction estimates possible future states, whereas risk assessment evaluates the significance of those states in terms of probability, severity, exposure, vulnerability, or operational consequence. For example, a predictive model may estimate that the workload of a system component will increase. Risk assessment is needed to determine whether the increase is likely to result in overload, service degradation, resource shortage, or broader system disruption.

The distinction can be expressed as follows:

$$\text{Future-State Prediction} \neq \text{Dynamic Risk Assessment}$$

Prediction provides information about possible future conditions, while risk assessment interprets the implications of those conditions for system operation. The two functions are related but should not be collapsed into a single analytical step.

This distinction has direct implications for resource orchestration. First, different predicted conditions may have different operational consequences even when their estimated probabilities are similar. Second, risk information can influence resource priorities by identifying components or processes that require preventive support. Third, risk assessment allows resource decisions to account for trade-offs between immediate efficiency and future stability.

Accordingly, the relevant decision transition can be represented as:

$$\text{Predicted Future State} \rightarrow \text{Dynamic Risk Assessment} \rightarrow \text{Risk-Sensitive Resource Orchestration}$$

The role of dynamic risk assessment in this transition is not merely to provide an additional performance indicator. It is to translate predictive information into decision-relevant information. This translation allows resource orchestration to respond to the anticipated consequences of future system conditions rather than relying exclusively on current demand or utilization.

A risk-aware orchestration process may therefore consider multiple performance dimensions simultaneously. Utility and cost describe efficiency-related outcomes, whereas risk, shortage, volatility, and constraint violation provide information about operational stability and the consequences of resource decisions. Their joint consideration is particularly relevant when system performance cannot be represented adequately by a single objective.

2.6.Closed-loop decision-making and feedback updating

Closed-loop decision-making connects system observation, analysis, action, system response, and subsequent updating. Unlike an open-loop process, in which decisions are generated without incorporating subsequent system feedback, a closed-loop process incorporates new observations and revises decisions as system conditions evolve.

Digital twins provide a suitable computational basis for such processes because their digital representations can be updated through interactions with the physical system. A closed-loop digital-twin decision process may involve observing the current system state, synchronizing the digital representation, predicting future conditions, assessing associated risks, orchestrating resources, observing the resulting system response, and updating the system representation and subsequent decisions. At a conceptual level, this process can be summarized as follows:

$$\text{System State} \rightarrow \text{Digital Twin Synchronization} \rightarrow \text{Future-State Prediction} \rightarrow \text{Dynamic Risk Assessment} \rightarrow \text{Resource Orchestration} \rightarrow \text{System Response} \rightarrow \text{Feedback Updating}$$

The feedback-updating stage returns new information to the subsequent decision cycle, allowing predictions, risk assessments, and resource decisions to be revised as system conditions evolve.

Research on reinforcement twinning has examined the relationship between digital twins and model-based reinforcement learning, illustrating how digital representations can support action evaluation and adaptive decision processes[21]. This line of research illustrates the potential of digital twins to support iterative decision-making rather than one-time analysis.

However, the presence of feedback does not, by itself, establish a risk-aware decision process. A system may update its state after an action without explicitly evaluating the risk implications of future conditions. Likewise, a learning-based controller may improve a selected performance objective while leaving risk, shortage, volatility, or constraint violations insufficiently represented in the decision process.

The closed-loop perspective adopted in this study therefore places particular emphasis on risk assessment as the transition mechanism between future-state prediction and resource orchestration. Feedback is used not only to update the digital representation of the system but also to improve subsequent prediction, risk evaluation, and resource decisions. In this sense, the closed loop is defined by the integration of system-state updating and risk-sensitive decision revision rather than by feedback alone.

2.7.Research gap and positioning of the present study

The reviewed literature indicates that digital twins have developed from descriptive and monitoring-oriented representations toward more intelligent systems capable of prediction, adaptive control, and resource optimization[10-17]. Existing studies have also investigated digital-twin-enabled resource allocation, dynamic scheduling, and iterative decision-making in different application contexts[18-21]. However, these research streams are not always integrated into a unified decision process for complex systems characterized by interdependencies, evolving conditions, and competing operational requirements.

In particular, existing digital-twin-based optimization studies tend to emphasize system performance, resource utilization, or scheduling efficiency, whereas risk is often represented as a separate assessment task, an additional constraint, or a secondary performance consideration[18-20]. Conversely, risk-aware decision-making may evaluate potential adverse conditions without establishing a direct mechanism through which predicted risk dynamically influences resource orchestration. Similarly, the presence of feedback does not necessarily imply that future-state prediction, dynamic risk assessment, and risk-sensitive resource revision are integrated into one continuous decision cycle[21]. These limitations suggest the need for a more explicit connection between predicted system conditions, dynamic risk evaluation, and subsequent resource decisions.

To address this gap, the present study develops an AI – digital twin framework for closed-loop risk-aware resource orchestration in complex systems. The framework links digital-twin synchronization, future-state prediction, dynamic risk assessment, resource orchestration, system response, and feedback updating within a unified decision cycle. Its central positioning is to treat dynamic risk assessment as the transition mechanism between predicted future conditions and resource orchestration, thereby allowing resource decisions to account not only for expected system performance but also for evolving risk, shortage, volatility, and operational constraints. The proposed framework is evaluated against static allocation and predictive allocation baselines using utility, cost, risk, shortage, volatility, and constraint violations as the principal evaluation dimensions.

3.Proposed methodology

3.1.Framework overview

Complex systems often operate under changing conditions, interdependent components, uncertain demand, and limited resources. Under such circumstances, resource decisions based only on current observations may become ineffective because the consequences of an action frequently emerge after a delay. A decision process that considers only the present state may therefore overlook future shortages, risk accumulation, operational instability, and constraint violations.

To address this problem, this study develops an AI–Digital Twin methodology for closed-loop, risk-aware resource orchestration. The methodology connects system-state representation, digital twin synchronization, future-state prediction, dynamic risk assessment, resource orchestration, system response, and feedback updating. Its central principle is that predicted future states should not be transferred directly to resource decisions. Instead, future-state predictions are first converted into a dynamic risk assessment, which serves as the transition mechanism between predictive intelligence and resource orchestration.

Let x_t denote the physical system state at decision time t , u_t the resource decision, w_t the external disturbance or uncertain influence, and G_t the relevant system-structure or interdependency information. The general state transition is represented as

$$x_{t+1}=f(x_t, u_t,w_t) \tag{1}$$

The methodology follows the sequence

$$x_t \rightarrow z_t \rightarrow \hat{x}_{t+1} \rightarrow r_t \rightarrow u_t^* \rightarrow x_{t+1} \rightarrow z_{t+1} \tag{2}$$

where z_t represents the synchronized digital twin state, $\hat{x}_{t+1}$ the predicted future state, r_t the dynamic risk assessment, and u_t^* the selected resource decision. The resulting system response is subsequently used to update the digital twin and support the next decision cycle.

The methodology is not designed as a standalone optimization algorithm. Rather, it provides a structured decision architecture in which artificial intelligence supports state prediction and risk estimation, while the digital twin maintains a synchronized representation of the physical system and facilitates feedback-based decision updating.

3.2.System-state representation and digital twin synchronization

3.2.1.System-state representation

A physical system is represented by its observable and decision-relevant state variables. The physical system itself is denoted by P ,while its physical state universe is denoted by X. At time t, the system occupies a particular state x_t where

$$x \in X \tag{3}$$

The distinction between P and X is important. The physical system P refers to the actual entity or operational environment, whereas X represents the set of admissible physical states that the system may occupy. The state x_t is therefore a time-specific realization within the state universe rather than the physical system itself.

Depending on the application, x_t may include resource availability, demand levels, workload, system capacity, service conditions, component status, or other operational variables. The methodology does not require a fixed state-vector structure for every application. Instead, the state representation should contain the information necessary for prediction, risk assessment, and resource decision-making.

The system evolves under the influence of decisions and external conditions. Here, u_t represents the resource allocation or orchestration decision, while w_t captures external disturbances, uncertain demand, environmental changes, or other influences not directly controlled by the decision-maker. The function $f(\cdot)$ expresses the underlying system transition.

3.2.2.Digital-twin representation

The digital twin provides a computational representation of the physical system and its current operational state. In the proposed methodology, the digital twin is represented by z_t. It contains synchronized information derived from the physical state, system structure, historical observations, and relevant data.

The digital twin representation is expressed as

$$z_t=\Phi(x_t,G_t,D_t;\theta) \quad (4)$$

where G_t denotes system-structure or interdependency information, D_t represents the available historical and observational data, and θ denotes the parameters associated with the digital-twin representation or learning process. The mapping $\Phi(\cdot)$ indicates that the digital twin is not merely a static copy of the physical state. It integrates state information with structural and data-related information to support prediction and decision-making.

The role of z_t is therefore operational rather than purely descriptive. It serves as the information interface through which the current physical system is represented, analyzed, and connected to future-state prediction.

3.2.3.Synchronization process

Digital twin synchronization is the process through which the computational representation is updated according to the current physical system. At each decision cycle, new observations are incorporated into the digital twin to reduce the discrepancy between the physical state and its computational representation.

The synchronization process can be summarized as

$$x_t \rightarrow z_t \quad (5)$$

The quality of this synchronization affects the reliability of subsequent prediction and risk assessment. If the digital twin is based on outdated or incomplete information, the predicted future state may not adequately reflect the current operating conditions. Consequently, synchronization is treated as a continuing process rather than a one-time initialization step.

The updated digital twin provides the information basis for future-state prediction, risk assessment, and resource orchestration. After the system responds to a selected decision, new observations are incorporated into the next digital twin state, thereby supporting the closed-loop structure described later in this chapter.

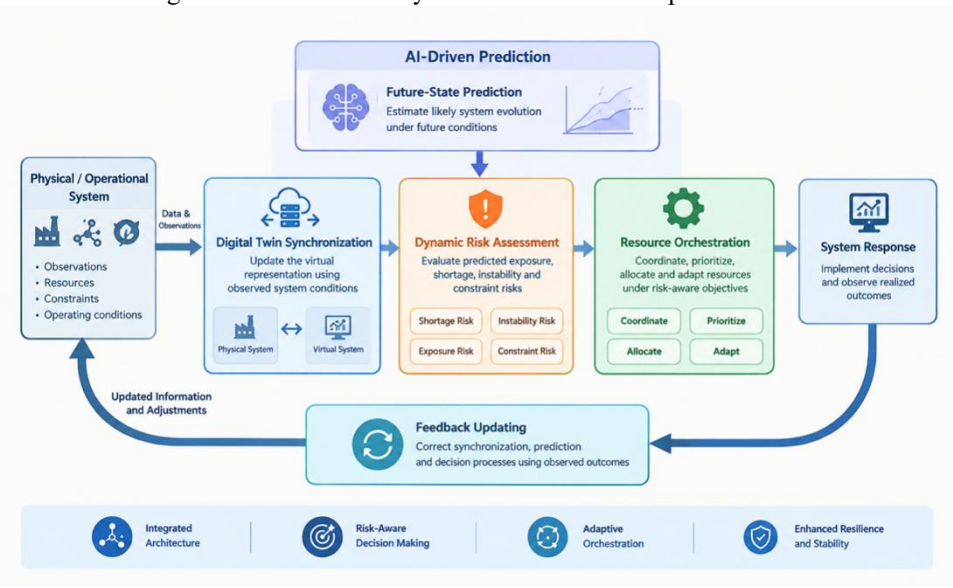


Fig 1. Closed-loop AI–digital twin architecture for risk-aware resource orchestration

3.3.Future-state prediction

3.3.1.Prediction objective

The purpose of future-state prediction is to estimate how the system may evolve beyond the current decision point. Rather than relying exclusively on x_t, the methodology uses the synchronized digital twin state z_t, together with relevant external information, to estimate the next system state.

The predicted future state is denoted by $\hat{x}_{t+1}$ and can be represented as

$$\hat{x}_{t+1}=F(z_t,w_t;\theta) \quad (6)$$

Here, F(·) denotes the prediction process, which may be implemented using an appropriate artificial intelligence or statistical learning method. The methodology does not require one specific learning architecture. The selection of a prediction method depends on the data structure, system characteristics, and application requirements.

The prediction process establishes the first forward-looking component of the methodology. It changes the decision basis from a purely reactive interpretation of the current state to an anticipatory assessment of possible future conditions.

3.3.2.Prediction and decision information

The predicted state $\hat{x}_{t+1}$ may contain information about expected demand, resource shortage, capacity pressure, service degradation, workload imbalance, or other future operational conditions. However, prediction alone does not determine the appropriate resource decision.

The relationship between prediction and decision-making is therefore expressed as

$$z_t \rightarrow \hat{x}_{t+1} \rightarrow r_t \quad (7)$$

This sequence indicates that the predicted state is first interpreted through a risk-assessment process before it is used for resource orchestration. The prediction stage provides information about what may happen, whereas the risk-assessment stage evaluates the operational significance and potential consequences of those predicted conditions.

This distinction prevents the methodology from treating prediction as an implicit decision rule. A predicted shortage, for example, does not automatically imply a particular allocation decision. Its decision relevance depends on severity, timing, system dependencies, resource cost, and the potential consequences of alternative actions.

3.3.3.Prediction uncertainty

Future-state prediction is subject to uncertainty arising from incomplete observations, model approximation, external disturbances, changing system conditions, and limitations in historical data. Therefore, $\hat{x}_{t+1}$ should be interpreted as an estimated future state rather than a guaranteed outcome.

The methodology accounts for this uncertainty through the subsequent dynamic risk-assessment stage. Instead of assuming that the predicted state is exact, the decision process evaluates the possible operational exposure associated with the predicted condition. This enables prediction uncertainty to influence resource decisions indirectly through the risk term.

Accordingly, prediction is not treated as an isolated forecasting task. Its value is realized when the estimated future state is transformed into decision-relevant risk information.

3.4.Dynamic risk assessment

3.4.1.Risk-assessment objective

Dynamic risk assessment evaluates the potential operational consequences associated with the predicted future state. It is designed to identify conditions that may threaten system performance, resource sufficiency, stability, or the satisfaction of operational constraints.

The risk assessment is represented by

$$r_t=R(\hat{x}_{t+1},x_t,G_t,u_t;\theta) \quad (8)$$

where $R(\cdot)$ denotes the risk-assessment process. The risk assessment considers the predicted future state, the current state, the system structure, and the relevant resource decision. The inclusion of u_t allows the risk assessment to reflect how alternative decisions may alter future exposure, provided that candidate decisions are evaluated within the decision process.

The resulting risk value r_t is dynamic because it changes with system conditions, predictions, interdependencies, and decision alternatives. It is therefore not treated as a fixed system attribute or a one-time risk score.

3.4.2.Risk dimensions

Depending on the application, dynamic risk may include several related dimensions:

- Shortage risk, reflecting the possibility that available resources will be insufficient to meet demand or operational requirements;
- Constraint-violation risk, reflecting the possibility that capacity, service, safety, or operational constraints will be exceeded;
- Volatility risk, reflecting instability or excessive fluctuation in resource demand, system performance, or allocation outcomes;
- Service or utility degradation risk, reflecting the possibility of reduced system utility or performance;
- Interdependency-related risk, reflecting the propagation of adverse effects across connected components or operational units;
- Accumulated operational risk, reflecting the persistence or accumulation of adverse conditions over successive decision cycles.

These dimensions need not be treated as independent. In an interconnected system, a shortage in one component may influence other components, while an aggressive allocation decision may reduce immediate shortage but increase cost or volatility. The role of dynamic risk assessment is to organize these consequences into decision-relevant information.

3.4.3.Risk as a decision-transition mechanism

The central methodological contribution is the explicit role of risk as a transition mechanism between future-state prediction and resource orchestration. Existing predictive approaches may estimate future demand or system conditions without formally translating those estimates into risk-sensitive resource decisions. Similarly, resource-scheduling approaches may optimize allocation based on current requirements without explicitly incorporating predicted risk.

The proposed sequence is

$$\hat{x}_{t+1} \rightarrow r_t \rightarrow u_t^* \quad (9)$$

The first arrow represents the transformation of future-state information into a risk assessment. The second arrow represents the use of that risk assessment in selecting a resource decision. Thus, the methodology does not equate prediction with orchestration. Instead, it introduces a distinct intermediate decision layer in which predicted consequences are evaluated before resources are allocated.

This structure also differentiates the methodology from a purely digital-twin-driven closed-loop optimization process. The digital twin supplies synchronized system information and supports feedback, but the decision transition is explicitly organized around dynamic risk derived from predicted future conditions. The contribution is consequently located in the integration of prediction, risk interpretation, and orchestration within one closed-loop decision process.

3.5.Risk-aware resource orchestration

3.5.1.Resource decision variables

Resource orchestration determines how available resources are allocated, adjusted, prioritized, or redirected in response to

predicted system conditions and assessed risks. The decision variable is denoted by u_t.

The feasible decision set is represented by U_t, which contains the resource decisions permitted under the operational conditions at time t. Thus,

$$u_t \in \mathrm{U}_t \tag{10}$$

The feasible set may be determined by resource availability, capacity limitations, service requirements, policy rules, timing restrictions, or other operational constraints. It can vary across decision cycles as system conditions change.

Resource orchestration is broader than static allocation. It may involve reallocating resources among components, prioritizing high-risk demands, adjusting resource levels, preserving reserve capacity, or balancing immediate utility against future exposure.

3.5.2.Utility and cost

The resource decision should account for both the benefits generated by resource allocation and the costs required to implement that allocation. Let $U_t(u_t)$ denote the utility associated with decision u_t, and let $C_t(u_t)$ denote its operational or resource cost.

Utility may reflect service fulfillment, demand satisfaction, system performance, recovery effectiveness, or other application-specific benefits. Cost may include resource consumption, allocation effort, delay, energy use, financial expenditure, or other operational burdens.

Because resource decisions may improve immediate utility while increasing future exposure, utility and cost alone are insufficient for risk-sensitive orchestration. The dynamic risk term is therefore incorporated into the decision objective.

3.5.3.Risk-aware objective function

The decision objective combines utility, cost, and dynamic risk:

$$J_t(u_t)=\alpha U_t(u_t)-\beta C_t(u_t)-\lambda r_t(u_t) \tag{11}$$

Where α, β, and λ are nonnegative weighting parameters that determine the relative importance of utility, cost, and risk.

The objective indicates that a desirable decision should generate operational utility while controlling resource cost and predicted risk exposure. The risk term does not necessarily replace utility maximization or cost minimization. Instead, it changes the decision preference by penalizing decisions associated with greater potential adverse consequences.

When the decision process explicitly evaluates feasible candidate decisions, the selected resource decision can be expressed as

$$u_t^*=argmax_{u_t \in \mathrm{U}_t} J_t(u_t) \tag{12}$$

The proposed decision formulation describes the decision principle rather than prescribing a particular optimization algorithm. Depending on the application, the maximization operation may be implemented through enumeration, rule-based selection, mathematical programming, heuristic search, or another suitable decision procedure. The essential requirement is that the selected decision should reflect the combined effects of utility, cost, and dynamic risk.

3.5.4.Operational constraints

Resource orchestration must remain consistent with the feasible operating conditions of the system. Typical constraints include:

(1). Resource-capacity constraints, ensuring that allocated resources do not exceed available capacity;

(2). Demand-satisfaction constraints, ensuring that critical requirements are adequately addressed;

(3). Balance constraints, ensuring that resources are distributed consistently across system components;

(4). Service constraints, ensuring that minimum service or performance levels are maintained;

(5). Temporal constraints, ensuring that decisions respect response and implementation times;

(6). Interdependency constraints, ensuring that decisions in one component do not create infeasible conditions in connected components.

These constraints define U_t and prevent the risk-aware objective from producing decisions that are mathematically attractive but operationally infeasible.

Risk-aware orchestration should therefore be understood as constrained decision-making. A decision with high nominal utility is not necessarily desirable if it creates severe shortage, instability, or constraint-violation exposure.

3.5.5.Interpretation of resource orchestration

The term orchestration emphasizes coordinated and adaptive resource management rather than isolated allocation. In a complex system, resource decisions may affect multiple components simultaneously, and their consequences may propagate through system interdependencies.

The orchestration process therefore considers not only the immediate allocation result but also the predicted system response and associated risk. This enables the decision process to prioritize resources according to future operational needs rather than relying solely on current demand or fixed allocation rules.

The methodology does not assume that every decision must produce the globally optimal allocation for the entire planning horizon. Instead, it supports repeated decision-making in which each decision is informed by the current synchronized state, predicted future conditions, dynamic risk, and subsequent feedback.

3.6.Closed-loop decision procedure

3.6.1.Decision cycle

The proposed methodology operates through repeated decision cycles. At each cycle, the physical system is observed, the digital twin is synchronized, the future state is predicted, risk is assessed, and a resource decision is selected. The system then responds to the decision, and the resulting observations are used to update the next cycle.

The complete closed-loop procedure is represented as

$$x_t \rightarrow z_t \rightarrow \hat{x}_{t+1} \rightarrow r_t \rightarrow u_t^* \rightarrow x_{t+1} \rightarrow z_{t+1} \tag{13}$$

Each transition has a distinct role:

$x_t \rightarrow z_t$: synchronization of the physical system with its digital representation;

$z_t \rightarrow \hat{x}_{t+1}$: prediction of the future system state;

$\hat{x}_{t+1} \rightarrow r_t$: transformation of prediction into dynamic risk information;
$r_t \rightarrow u_t^*$: selection of a risk-aware resource decision;
$u_t^* \rightarrow x_{t+1}$: physical system response to the selected decision;
$x_{t+1} \rightarrow z_{t+1}$: updating of the digital twin using new system observations.

This cycle allows the decision process to adapt to changing conditions rather than applying a fixed decision rule throughout the entire operating period.

3.6.2.Feedback updating

Feedback updating incorporates the observed system response into the next decision cycle. After u_t^* is implemented, the resulting state x_{t+1} is observed and used to update z_{t+1} . The updated digital twin may then support revised prediction, risk assessment, and resource orchestration.

Feedback is important for at least three reasons. First, it allows the methodology to respond to discrepancies between predicted and observed system behavior. Second, it enables the digital twin to reflect changing system conditions. Third, it supports the accumulation of operational information across decision cycles.

The feedback mechanism does not imply that every prediction will be exact. Instead, it provides a means of correcting the decision process as new information becomes available.

3.6.3.Closed-loop versus open-loop decision-making

In an open-loop decision process, resource decisions are determined in advance or are based primarily on current information, with limited adjustment after the system responds. Such a process may perform adequately under stable conditions but can become less effective when demand, disturbances, or system dependencies change.

The proposed methodology is closed-loop because the system response is returned to the digital twin and influences subsequent prediction and decision-making. Its distinguishing feature is not simply the presence of feedback, but the integration of feedback with future-state prediction and dynamic risk assessment.

Accordingly, the methodology can be summarized as a predictive and risk-aware closed-loop process rather than a purely reactive allocation scheme:

Synchronization→Prediction→Risk Assessment→Orchestration→Response→Feedback

3.7.Methodological scope and experimental operationalization

The methodology developed in this chapter is evaluated through a controlled comparison of three resource-decision strategies: static allocation, predictive allocation, and risk-aware orchestration. These strategies represent progressively different levels of decision support and are used to distinguish the contribution of future-state information from the additional contribution of explicit risk integration.

3.7.1.Static allocation

Static allocation provides a nonadaptive reference strategy. Resource decisions are determined using predefined rules, fixed allocation proportions, or initial operating conditions, without explicitly incorporating future-state prediction or dynamic risk assessment.

This strategy establishes a baseline against which the benefits of adaptive decision-making can be assessed. Its purpose is not to represent all conventional allocation methods, but to provide a reference case in which resource assignments are not systematically revised in response to predicted changes in system conditions.

3.7.2.Predictive allocation

Predictive allocation introduces future-state information into the decision process. Resource decisions are adjusted according to predicted demand, workload, capacity pressure, or other expected system conditions.

This strategy represents a forward-looking decision process, but it does not explicitly incorporate the risk-assessment transition used in the proposed methodology. Consequently, it allows the evaluation to determine whether the use of prediction alone is sufficient to improve system performance, or whether additional benefits arise from integrating predicted conditions with dynamic risk assessment.

3.7.3.Risk-aware orchestration

Risk-aware orchestration represents the complete decision strategy examined in this study. It combines synchronized system information, future-state prediction, dynamic risk assessment, and adaptive resource decision-making within a feedback-based operating process.

In contrast to predictive allocation, this strategy evaluates predicted system conditions in terms of their potential operational consequences before resource decisions are selected. The resulting decisions are therefore informed not only by expected future conditions but also by the associated risks, resource costs, and operational constraints.

The experimental comparison focuses on six evaluation dimensions:

- Utility, representing the operational benefit or performance achieved by the resource decisions;
- Cost, representing resource consumption or operational expenditure;
- Risk, representing the magnitude of adverse operational exposure;
- Shortage, representing unmet demand or insufficient resource availability;
- Volatility, representing instability or excessive fluctuation in resource allocation or system performance;
- Constraint violation, representing the frequency or magnitude of infeasible operating conditions.

These dimensions are selected to assess both the benefits and the operational consequences of each strategy. Utility and cost capture the principal performance trade-off, while risk, shortage, volatility, and constraint violation provide a broader assessment of operational robustness.

The comparison is therefore intended to answer two related questions. First, does incorporating future-state information improve resource decisions relative to static allocation? Second, does the explicit integration of dynamic risk provide additional benefits beyond prediction alone?

3.8. Chapter summary

This chapter established the mathematical and operational basis of the proposed AI–Digital Twin methodology. It defined the physical system state, digital twin representation, future-state prediction, dynamic risk assessment, risk-aware resource orchestration, and feedback-based decision updating.

The methodology treats dynamic risk assessment as the central transition between predicted future conditions and resource decisions. Its evaluation is operationalized through three strategies—static allocation, predictive allocation, and risk-aware orchestration—and six evaluation dimensions: utility, cost, risk, shortage, volatility, and constraint violation.

The following chapters present the experimental configuration, comparative results, and discussion of the methodological implications.

4. Experimental design and simulation setup

4.1. Experimental objectives and overall design

This study employs a controlled simulation experiment to evaluate whether the proposed AI–Digital Twin approach can improve risk-aware resource decision-making under changing operating conditions and uncertainty. The experimental design addresses three related questions. First, does the incorporation of future-state prediction improve resource allocation compared with a static allocation strategy? Second, does the explicit integration of dynamic risk assessment provide additional benefits beyond prediction-based allocation? Third, does the proposed closed-loop mechanism, which combines Digital Twin synchronization, risk-aware orchestration, and feedback updating, provide further improvements over a risk-aware decision process without the complete closed-loop integration?

To address these questions, four decision strategies are compared: static allocation, predictive allocation, risk-aware orchestration, and the proposed closed-loop risk-aware orchestration. All strategies operate within the same simulated physical system, share the same initial conditions and resource limitations, and are evaluated over the same decision horizon. The strategies differ only in the mechanisms used to process system information, anticipate future conditions, assess risk, and update resource decisions.

Static allocation represents a nonadaptive baseline that does not explicitly respond to predicted system evolution. Predictive allocation introduces future-state information into the decision process but does not explicitly integrate dynamic risk into resource decisions. Risk-aware orchestration incorporates predicted risk into resource decision-making but does not include the complete closed-loop integration of synchronization, orchestration, and feedback updating. The proposed closed-loop risk-aware orchestration integrates Digital Twin synchronization, future-state prediction, dynamic risk assessment, resource coordination, and feedback updating into a repeated decision process.

Performance is assessed across six dimensions: utility, cost, risk, shortage, volatility, and constraint violation. These dimensions are selected to capture both the benefits and the potential trade-offs of risk-aware resource decision-making. Utility reflects the effectiveness of resource utilization, while cost represents the resource expenditure associated with each decision. Risk captures the overall decision-related exposure, shortage reflects unmet resource requirements, volatility indicates fluctuations in system performance or resource allocation, and constraint violation measures the extent to which operational limitations are breached.

The experimental design therefore separates the contributions of future-state prediction, risk-aware decision integration, and closed-loop feedback updating. The comparison between static and predictive allocation evaluates the contribution of prediction. The comparison between predictive allocation and risk-aware orchestration examines the additional value of explicitly incorporating risk into decision-making. Finally, the comparison between risk-aware orchestration and the proposed closed-loop risk-aware orchestration evaluates whether synchronization and feedback updating provide additional benefits beyond risk-aware decision integration alone.

4.2. Simulation environment and scenario configuration

The simulation represents a dynamic complex system whose physical state changes over discrete decision periods. Let P denote the physical system and X its physical state universe, with the system state at period t represented by $x_t \in X$. The state includes relevant information concerning resource availability, demand, workload, service performance, capacity pressure, resource shortage, and other operational conditions. System interdependencies are represented by G_t, while w_t denotes external disturbances and uncertain influences affecting system evolution.

The physical system follows the general state-transition relationship

$$x_{t+1}=f(x_t, u_t, w_t) \tag{14}$$

Where denotes the resource decision applied at period t. The simulation uses time-varying demand and resource conditions rather than a fixed operating environment. The scenarios include normal operating periods, demand growth, sudden demand surges, uneven resource requirements, and disturbance-affected periods. These conditions are intended to create variations in resource pressure and operational risk while remaining sufficiently controlled for comparative evaluation.

Resource availability is constrained, and feasible decisions must satisfy

$$u_t \in U_t \tag{15}$$

where U_t denotes the feasible decision set at period *t*. The set reflects available resources, capacity limitations, operational requirements, and other constraints. The same resource limits, demand sequences, disturbance conditions, and system interdependencies are applied to all three strategies. This design ensures that performance differences are attributable to the decision mechanisms rather than to unequal experimental conditions.

The simulation is organized into discrete decision cycles. At each period, the current physical state is observed, the digital twin is updated, the next state is predicted, risk is assessed, a resource decision is selected, and the resulting

system response is recorded. The resulting state is then used in the next cycle, allowing the experiment to evaluate both immediate decision quality and cumulative performance over time.

4.3.Digital twin, prediction, and risk configuration

The digital twin provides a computational representation of the current physical system by integrating the observed state, system structure, available data, and model parameters. Its representation is defined as

$$z_t=\Phi(x_t,G_t,D_t;\theta) \tag{16}$$

where z_t is the digital-twin state, D_t denotes the data available at period t, and θ represents the parameters of the representation and prediction process.

Based on the synchronized digital-twin state, the next physical state is predicted as

$$\hat{x}_{t+1}=F(z_t,w_t;\theta) \tag{17}$$

The prediction provides forward-looking information about possible demand, capacity, shortage, service, and system-performance conditions. In the experiment, prediction is performed before the resource decision is made. The predictive allocation strategy uses the predicted state to guide allocation, whereas the risk-aware orchestration strategy further evaluates the operational consequences of candidate decisions.

Dynamic risk is represented as a decision-dependent quantity:

$$r_t(u_t)=R(\hat{x}_{t+1},x_t,G_t,u_t;\theta) \tag{18}$$

This formulation allows risk to reflect not only the predicted future state but also the current state, system interdependencies, and the resource decision being considered. The risk assessment considers several operational dimensions, including shortage exposure, capacity pressure, potential service degradation, interdependency-related exposure, system instability, and constraint-related risk. The same risk representation and normalization procedure are used throughout the risk-aware experiments.

The methodological distinction among the three strategies is therefore expressed as follows. Static allocation does not explicitly use future-state prediction or dynamic risk assessment. Predictive allocation uses the predicted state $\hat{x}_{t+1}$ but does not explicitly incorporate a decision-dependent risk term. Risk-aware orchestration integrates prediction and risk assessment before selecting the resource decision. In this way, risk functions as a transition mechanism between future-state intelligence and resource orchestration rather than as a separate descriptive indicator.

4.4.Comparative decision strategies

The experiment compares the following three strategies.

Static allocation. The static strategy allocates resources according to predefined proportions, fixed rules, or current-period requirements. Its decisions do not adapt explicitly to predicted future conditions or dynamically assessed risk. This strategy serves as the baseline for evaluating the value of adaptive decision-making.

Predictive allocation. The predictive strategy uses the predicted future state $\hat{x}_{t+1}$ to adjust resource allocation. Its decision process can be summarized as

$$z_t\rightarrow\hat{x}_{t+1}\rightarrow u_t^* \tag{19}$$

This strategy captures the benefit of forward-looking information but does not explicitly evaluate the risk associated with each candidate decision.

Risk-aware orchestration. The proposed strategy integrates the synchronized digital twin, future-state prediction, dynamic risk assessment, and resource orchestration. Its decision objective is defined as

$$J_t(u_t)=\alpha U_t(u_t)-\beta C_t(u_t)-\lambda r_t(u_t) \tag{20}$$

subject to

$$u_t\in U_t \tag{21}$$

The selected decision is therefore expressed as

$$u_t^*=argmax_{u_t\in U_t}J_t(u_t) \tag{22}$$

Here, $U_t(u_t)$ denotes the utility generated by the decision, $C_t(u_t)$ denotes its cost, and $r_t(u_t)$ denotes the corresponding dynamic risk. The coefficients α, β, and λ determine the relative importance of utility, cost, and risk. The objective does not imply that risk is minimized independently of operational performance; rather, it embeds risk directly into the resource decision so that utility gains are evaluated together with their potential operational consequences.

The three strategies are implemented under comparable decision and resource constraints. The proposed strategy is not treated as a separate application-specific scheduling algorithm. Instead, it is evaluated as a closed-loop decision mechanism that combines state synchronization, prediction, risk assessment, and adaptive resource selection.

4.5.Evaluation metrics and experimental procedure

The performance of the three strategies is evaluated using six complementary metrics. Utility measures the operational benefit generated by resource decisions, while cost measures the resources or operational expenditure required to achieve that benefit. Risk measures the cumulative exposure associated with the selected decisions. Shortage captures unmet resource or service requirements. Volatility measures the degree of fluctuation in resource decisions across consecutive periods. Constraint violation records the frequency or magnitude of decisions that fail to satisfy predefined operational requirements.

For a decision horizon of T periods, cumulative utility, cost, and risk are calculated as

$$U_{total}=\sum_{t=1}^{T}U_t(u_t) \tag{23}$$

$$C_{total}=\sum_{t=1}^{T}C_t(u_t) \tag{24}$$

$$R_{total}=\sum_{t=1}^{T}r_t(u_t) \tag{25}$$

Cumulative shortage is calculated as

$$S_{total}=\sum_{t=1}^{T}S_t \tag{26}$$

Where S_t denotes the shortage recorded at period t. Decision volatility is measured by the cumulative change between consecutive resource decisions:

$$V_{total}=\sum_{t=1}^{T}\|u_t-u_{t-1}\| \tag{27}$$

Constraint violation is recorded according to the predefined operational constraints and is summarized over the complete decision horizon. These metrics are reported separately rather than being reduced to a single aggregate score, because a

strategy may improve utility while increasing cost, risk, or decision volatility.

The experimental procedure consists of the following repeated steps:

(1). Initialize the physical system and the corresponding digital-twin representation.

(2). Observe the current state x_t.

(3). Update the digital-twin state z_t.

(4). Predict the next state $\hat{x}_{t+1}$.

(5). Assess dynamic risk where required by the decision strategy.

(6). Select the resource decision u_t^* according to the relevant strategy.

(7). Apply the decision to the simulated physical system.

(8). Record the resulting system response and evaluation metrics.

(9). Use the updated state to begin the next decision cycle.

Each strategy is evaluated using the same initial state, decision horizon, demand sequence, resource availability, disturbance conditions, and interdependency structure. Repeated trials with different controlled scenario realizations are used to reduce the influence of any single disturbance sequence. The results are reported using the mean and dispersion of each metric across trials.

For metrics where a higher value indicates better performance, relative improvement is calculated as

$$Improvement(\%)=\frac{M_{proposed}-M_{baseline}}{M_{baseline}}\times 100 \quad (28)$$

For metrics where a lower value indicates better performance, relative reduction is calculated as

$$Reduction(\%)=\frac{M_{baseline}-M_{proposed}}{M_{baseline}}\times 100 \quad (29)$$

The comparative analysis considers both statistical and practical significance. In addition to mean differences, the analysis reports variability, effect magnitude where appropriate, and the consistency of the observed performance across repeated trials. Statistical tests are selected according to the final structure of the experimental observations and are applied consistently across the compared strategies.

4.6.Reproducibility and chapter summary

To support reproducibility, the experiment records the decision horizon, initial system state, resource capacities, demand-generation process, disturbance settings, system interdependencies, digital-twin configuration, prediction settings, risk-assessment parameters, utility and cost definitions, metric calculations, number of repeated trials, and random seeds. All strategies are evaluated under the same experimental protocol, and the implementation details required to reproduce the simulation are reported with the numerical results.

In summary, this chapter established the experimental design for evaluating the proposed AI–Digital Twin decision mechanism. A controlled dynamic simulation was defined, three decision strategies were specified, and six evaluation dimensions were selected to capture operational performance, resource expenditure, risk exposure, shortage, decision stability, and constraint compliance. The next chapter presents the simulation results and examines whether the integration of dynamic risk assessment produces measurable improvements beyond static and prediction-only allocation.

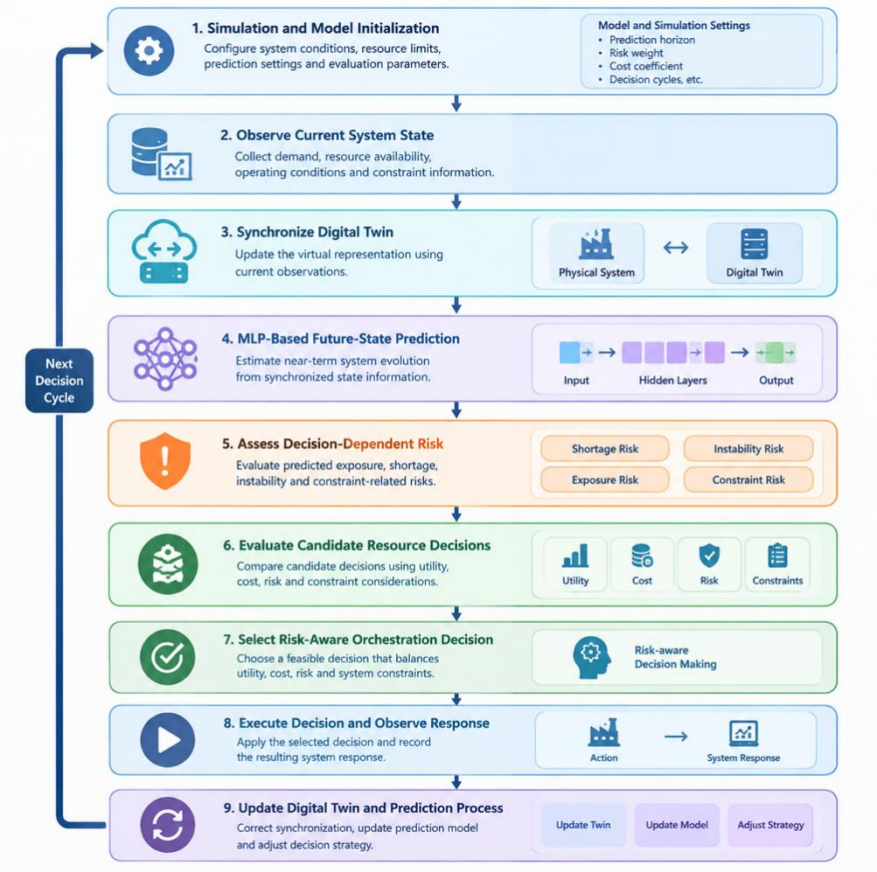


Fig 2. Computational workflow for AI–digital twin-based risk-aware resource orchestration

5.Computational experiments and results

5.1.Experimental design and configuration

The computational experiments evaluate the effectiveness of the proposed closed-loop risk-aware orchestration mechanism under dynamic system disturbances. The evaluation is structured to examine the progressive contribution of future-state prediction, risk-aware decision-making, digital-twin synchronization, and feedback updating.

The experimental workflow follows the proposed closed-loop sequence:

Observation→Twin Synchronization→Prediction→Risk Assessment→Orchestration→System Response→Feedback Updating

The experimental workflow follows the proposed closed-loop sequence:

Observation→Twin Synchronization→Prediction→Risk Assessment→Orchestration→System Response→Feedback Updating.

Four strategies are considered:

(1). Static Allocation, which applies a predefined allocation policy without future-state prediction or dynamic risk adaptation;

(2). Predictive Allocation, which incorporates predicted future states into resource allocation but does not explicitly integrate dynamic risk assessment into the decision process;

(3). Risk-Aware Orchestration, which combines future-state prediction with risk-sensitive resource orchestration but does not implement the complete synchronization – feedback mechanism;

(4). Proposed Closed-Loop Risk-Aware Orchestration, which integrates digital-twin synchronization, future-state prediction, dynamic risk assessment, resource orchestration, and feedback updating.

The first three strategies constitute the baseline conditions, whereas the fourth represents the complete proposed approach.

Each strategy was evaluated over 120 decision cycles per run using 12 independent random seeds. The complete comparative experiment therefore comprised 48 runs and 5,760 time-step observations.

The prediction module was implemented using a multilayer perceptron (MLP) trained on state-action-disturbance observations. The network used a 12-dimensional input, two hidden layers with 48 and 24 neurons, and ReLU activation functions. Adam optimization was used with a learning rate of 0.003 and a batch size of 256. Early stopping was applied during training.

The initial risk-weight parameter and the cost coefficient in the orchestration objective were set to

$$H=4 \tag{30}$$

The initial risk-weight parameter and the cost coefficient in the orchestration objective were set to

$$\beta_0=0.45,\ \alpha=0.12 \tag{31}$$

Here, β_0 denotes the initial risk weight, while the complete proposed strategy permits the risk weight β_t to be updated during the closed-loop process. The MLP achieved a training fit of approximately 0.9848, confirming that the prediction component was trained from generated system data rather than being based exclusively on a manually specified forecasting rule.

Table 2. Main comparative results

Strategy	Utility ↑	Cost ↓	Shortage ↓	Volatility ↓	Constraint Violation ↓	Risk ↓
Static Allocation	0.2002 ± 0.0084	0.1225 ± 0.0000	0.6549 ± 0.0144	0.0752 ± 0.0032	0.4779 ± 0.0217	0.4569 ± 0.0125
Predictive Allocation	0.2520 ± 0.0053	0.4994 ± 0.0083	0.5658 ± 0.0090	0.0806 ± 0.0023	0.3658 ± 0.0102	0.3845 ± 0.0067
Risk-Aware Orchestration	0.2705 ± 0.0043	0.6414 ± 0.0139	0.5339 ± 0.0072	0.0829 ± 0.0021	0.3248 ± 0.0075	0.3585 ± 0.0052
Proposed Closed-Loop	0.2768 ± 0.0049	0.6768 ± 0.0173	0.5230 ± 0.0082	0.0828 ± 0.0032	0.3128 ± 0.0084	0.3499 ± 0.0062

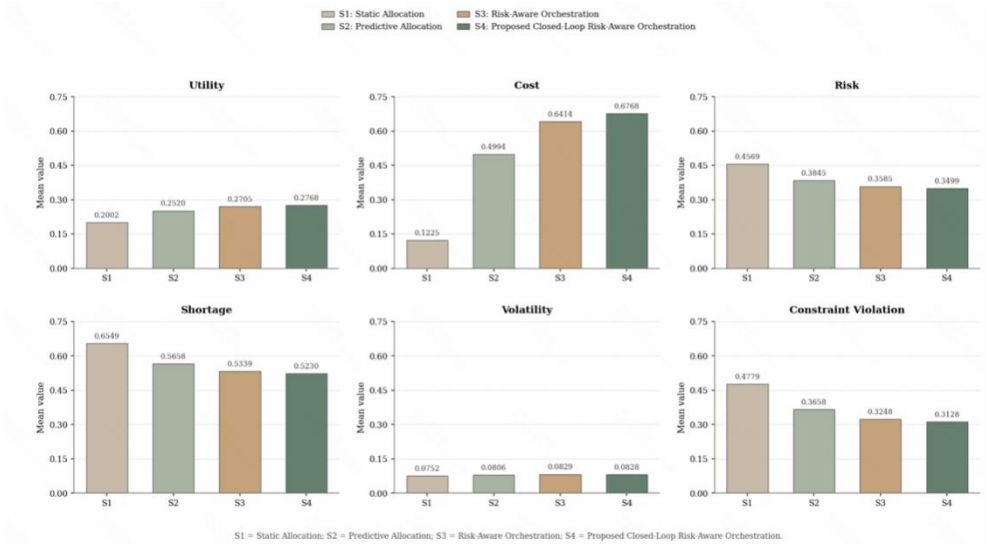


Fig 3. Comparative performance of the four decision strategies across six evaluation dimensions

Performance was evaluated using six metrics: Utility, Cost, Shortage, Volatility, Constraint Violation, and Risk. Utility is maximized, whereas the other metrics are minimized. The reported Risk value is the aggregate composite-risk measure obtained from the period-specific risk values $r_t(u_t)$.

5.2.Thompson sampling

Table 2 presents the mean and standard deviation obtained from the 12 independent runs for each strategy.

5.2.1.Predictive allocation and the contribution of future-state information

Predictive Allocation improves substantially upon Static Allocation. Utility increases from 0.2002 to 0.2520, while shortage decreases from 0.6549 to 0.5658. Constraint violation and composite risk decrease from 0.4779 to 0.3658 and from 0.4569 to 0.3845, respectively.

This performance difference demonstrates the value of incorporating future-state information into resource allocation under dynamic disturbances. Rather than relying exclusively on a predefined allocation rule, the predictive strategy accounts for anticipated system conditions when determining resource actions.

The improvement is associated with an increase in cost from 0.1225 to 0.4994. Thus, prediction improves the operational performance of the system but does not eliminate the underlying trade-off between resource expenditure and system outcomes.

5.2.2.Risk-aware orchestration and the role of risk assessment

Risk-Aware Orchestration further improves upon Predictive Allocation. Its mean utility reaches 0.2705, compared with 0.2520 for Predictive Allocation. Shortage decreases from 0.5658 to 0.5339, constraint violation decreases from 0.3658 to 0.3248, and composite risk decreases from 0.3845 to 0.3585.

The progression from Predictive Allocation to Risk-Aware Orchestration supports the role of risk assessment in converting predicted future states into decision-relevant information. Prediction provides an estimate of future system conditions, whereas risk-aware orchestration incorporates the potential consequences of those conditions into resource decisions.

The corresponding increase in cost, from 0.4994 to 0.6414, reflects the additional resource deployment associated with risk-sensitive decision-making.

5.2.3.Closed-loop orchestration and incremental performance gains

The comparison between Risk-Aware Orchestration and Proposed Closed-Loop isolates the additional contribution of the synchronization–feedback mechanism. Both strategies use prediction and risk-aware decision-making, but the proposed strategy additionally incorporates digital-twin synchronization, feedback correction, and dynamic updating.

Compared with Risk-Aware Orchestration, the Proposed Closed-Loop strategy produces the following changes:

- Utility increases from 0.2705 to 0.2768;
- Shortage decreases from 0.5339 to 0.5230;
- Constraint violation decreases from 0.3248 to 0.3128;
- Composite risk decreases from 0.3585 to 0.3499;
- Cost increases from 0.6414 to 0.6768;
- Volatility remains almost unchanged, decreasing from 0.0829 to 0.0828.

Based on the unrounded experimental means, the proposed strategy increases utility by approximately 2.34% and reduces composite risk by approximately 2.39% relative to Risk-Aware Orchestration. The corresponding increase in resource deployment cost is approximately 5.52%.

These results indicate that the closed-loop mechanism provides an incremental improvement beyond prediction and risk-aware orchestration alone. The improvement is concentrated in utility, shortage, constraint violation, and composite risk, whereas volatility remains largely unchanged. The contribution of the proposed approach is therefore best characterized as an improvement in the utility–risk trade-off through the integration of synchronization and feedback updating, rather than as uniform improvement across every performance dimension.

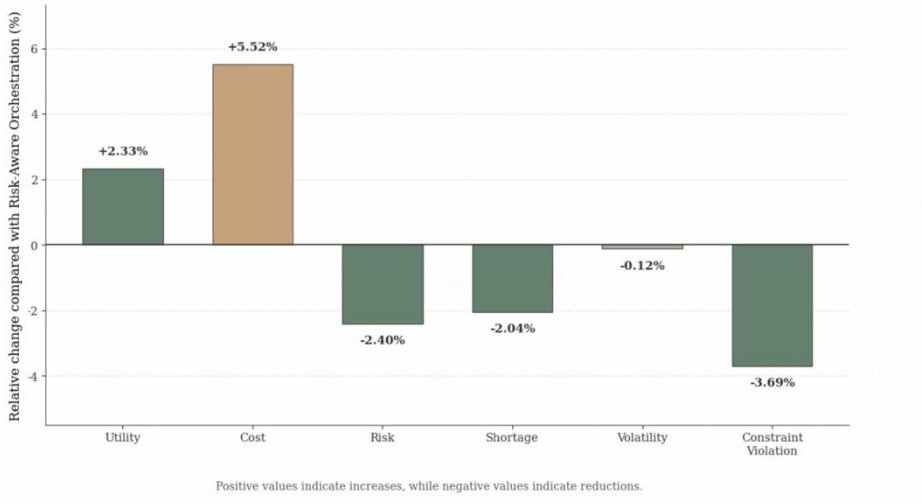


Fig 4. Relative performance changes of the proposed closed-loop orchestration compared with risk-aware orchestration

Figure 4 presents the relative changes achieved by the proposed closed-loop orchestration strategy compared with the risk-aware orchestration baseline. The proposed method improves utility by approximately 2.33% while reducing risk by approximately 2.40%, shortage by 2.04%, and constraint violation by 3.69%. Volatility changes only marginally, with a

relative reduction of approximately 0.12%. The 5.52% increase in cost reflects the additional resource expenditure associated with continuous feedback updating and adaptive orchestration. Overall, the results suggest that the proposed closed-loop mechanism generates measurable improvements in system effectiveness and risk control at the expense of a moderate increase in resource cost.

5.3.Statistical significance analysis

Paired Wilcoxon signed-rank tests were conducted to examine the differences between Proposed Closed-Loop and Risk-Aware Orchestration. The tests were performed using 12 seed-matched, run-level outcomes for each metric.

At the 0.05 significance level, the differences in Utility, Cost, Shortage, Constraint Violation, and Risk are statistically significant. The difference in Volatility is not statistically significant.

The statistical results reinforce the main comparative findings. The proposed strategy provides statistically distinguishable improvements in utility, shortage, constraint violation, and composite risk, while the associated cost increase is also statistically significant. In contrast, the observed difference in volatility is not statistically supported.

Table 3. Wilcoxon signed-rank test results

Metric	p-value	Significance at p<0.05
Utility	0.000488	Yes
Cost	0.000488	Yes
Shortage	0.000488	Yes
Volatility	0.791016	No
Constraint Violation	0.000488	Yes
Risk	0.000488	Yes

Accordingly, the evidence supports the conclusion that the proposed closed-loop mechanism improves the principal utility- and risk-related outcomes relative to Risk-Aware Orchestration, but does not establish a significant volatility improvement under the present experimental configuration.

5.4.Ablation study

5.4.1.Ablation configuration

An ablation study was conducted to assess the contribution of the principal components of the proposed closed-loop mechanism. The following variants were evaluated:

- Proposed-NoTwinSync: digital-twin synchronization is removed;
- Proposed-FixedBeta: the risk weight is fixed rather than dynamically updated;
- Proposed-NoFeedbackCorrection: synchronization is retained, but feedback correction is removed;
- Proposed-Full: all components of the proposed closed-loop mechanism are retained.

The main comparative experiment and the ablation experiment were evaluated under separate experimental protocols. Proposed-Full denotes the complete implementation within the ablation protocol.

Table 4. Ablation results

Variant	Utility ↑	Cost ↓	Shortage ↓	Volatility ↓	Constraint Violation ↓	Risk ↓
Proposed-NoTwinSync	0.2733	0.6616	0.5295	0.0841	0.3211	0.3556
Proposed-FixedBeta	0.2785	0.6826	0.5205	0.0848	0.3128	0.3493
Proposed-NoFeedbackCorrection	0.2711	0.6360	0.5334	0.0842	0.3266	0.3591
Proposed-Full	0.2787	0.6840	0.5202	0.0855	0.3115	0.3489

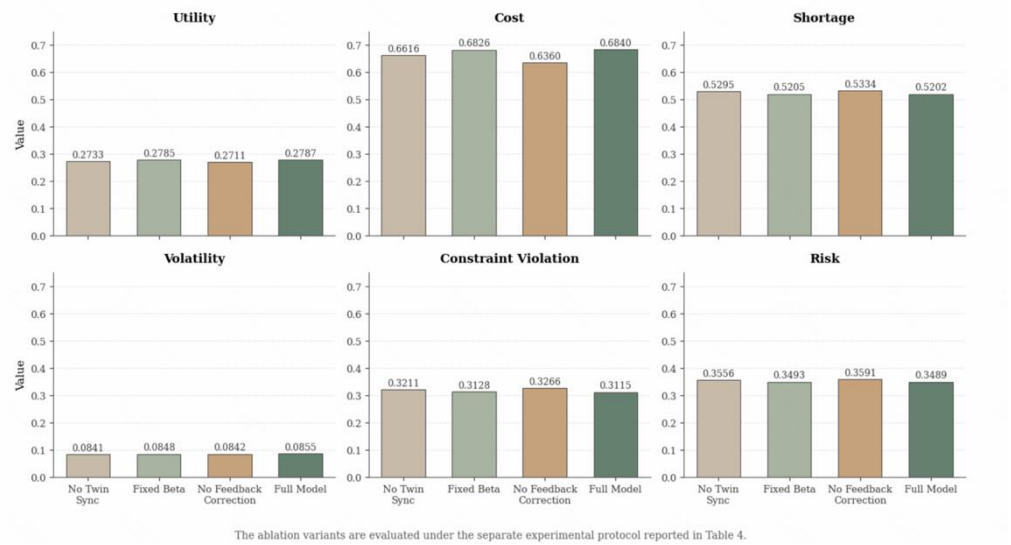


Fig 5. Ablation analysis of the proposed closed-loop orchestration mechanism

Figure 5 shows the performance profiles of the four ablation variants across the six evaluation dimensions. Proposed-Full achieves the highest utility value of 0.2787 and the lowest values of shortage, constraint violation, and composite risk, at 0.5202, 0.3115, and 0.3489, respectively. These results are consistent with the role of the complete closed-loop configuration in coordinating state representation, risk-sensitive decision-making, and feedback-based adjustment. Proposed-NoTwinSync records lower utility and higher shortage, constraint violation, and risk than Proposed-Full, while Proposed-NoFeedbackCorrection exhibits the largest deterioration in these principal performance measures. Proposed-FixedBeta produces results close to those of Proposed-Full, indicating that dynamic risk-weight adjustment provides a relatively modest incremental contribution under the present experimental configuration. The comparison therefore highlights the greater importance of synchronized state representation and feedback correction, while also showing that the complete mechanism involves a trade-off between performance improvement and resource deployment cost.

5.4.2.Effect of twin synchronization

Removing twin synchronization reduces utility from 0.2787 to 0.2733 and increases composite risk from 0.3489 to 0.3556. Shortage and constraint violation also increase, from 0.5202 to 0.5295 and from 0.3115 to 0.3211, respectively.

The result indicates that twin synchronization contributes to the quality of the system-state representation used by the prediction, risk assessment, and orchestration stages. Its contribution is reflected primarily in the improved risk-related outcomes of the complete model.

5.4.3.Effect of feedback correction

The removal of feedback correction produces the most pronounced deterioration among the principal ablation variants. Compared with Proposed-Full, Proposed-NoFeedbackCorrection reduces utility from 0.2787 to 0.2711. Shortage increases from 0.5202 to 0.5334, constraint violation increases from 0.3115 to 0.3266, and composite risk increases from 0.3489 to 0.3591.

This pattern supports the role of feedback correction in incorporating realized system responses into subsequent orchestration decisions. Without feedback correction, the policy is less able to adjust its decisions in response to discrepancies between predicted and realized system conditions.

The result provides direct empirical support for the closed-loop component of the proposed architecture.

5.4.4.Effect of dynamic risk-weight adjustment

The Proposed-FixedBeta variant achieves a composite risk of 0.3493, compared with 0.3489 for Proposed-Full. The complete model also produces slightly lower shortage and constraint violation, although these differences are small. At the same time, Proposed-Full incurs slightly higher cost and volatility.

The results indicate that dynamic risk-weight adjustment provides a modest incremental contribution under the present configuration. The larger performance difference is associated with the integrated synchronization–feedback mechanism. Therefore, the experimental evidence does not support attributing the overall improvement of the proposed approach to dynamic risk weighting alone.

5.5.Discussion

The comparative and ablation results provide evidence for the progressive structure of the proposed decision mechanism.

The comparison between Static Allocation and Predictive Allocation demonstrates that future-state prediction improves resource decisions under dynamic disturbances. The subsequent improvement obtained by Risk-Aware Orchestration indicates that predicted information becomes more effective when incorporated into an explicit risk-sensitive decision process.

The comparison between Risk-Aware Orchestration and Proposed Closed-Loop further shows that synchronization and feedback updating provide additional performance gains. Although the magnitude of the improvement is smaller than the gains obtained when moving from static allocation to prediction and then to risk-aware orchestration, it is consistently reflected in the principal operational metrics: utility, shortage, constraint violation, and composite risk.

The ablation results provide additional insight into the internal structure of the proposed method. Removing twin synchronization leads to a deterioration in risk-related performance, while removing feedback correction produces a more pronounced decline in utility and system-risk outcomes. In contrast, fixing the risk weight produces only a small change relative to the complete model. This suggests that the principal contribution of the proposed architecture lies in the interaction between synchronized state representation and feedback-based decision updating, rather than in dynamic risk-weight adjustment considered independently.

The results also establish an explicit utility–cost trade-off. The proposed strategy achieves improved utility and lower risk-related losses through increased resource deployment. This trade-off is a substantive part of the proposed decision problem rather than an experimental weakness: risk-aware orchestration is intended to identify resource actions that balance system utility, deployment cost, and risk exposure under dynamic constraints.

Nevertheless, the proposed strategy does not improve every metric. Volatility remains almost unchanged in the main comparison, and the corresponding statistical test is not significant. The findings therefore support a targeted interpretation of the proposed mechanism: it improves the utility–risk balance and reduces shortage and constraint violations, but it does not guarantee simultaneous improvement in all dimensions of system dynamics.

5.6.Chapter summary

This chapter evaluated four resource-allocation strategies using 120 decision cycles per run, 12 random seeds per strategy, 48 total runs, and 5,760 time-step observations. A trained MLP prediction module was used to provide future-state information for the predictive and risk-aware strategies.

The main results show that the Proposed Closed-Loop strategy achieves the highest mean utility and the lowest shortage, constraint violation, and composite risk among the four main comparative strategies. Relative to Static Allocation, it improves utility by approximately 38.26% and reduces composite risk by approximately 23.42%. Relative to Risk-Aware Orchestration, it further improves utility by approximately 2.34% and reduces composite risk by approximately 2.39%, while increasing resource deployment cost by approximately 5.52%.

The statistical analysis confirms significant differences in utility, cost, shortage, constraint violation, and risk, but not in volatility. The ablation study further indicates that feedback correction provides a more substantial contribution than dynamic risk-weight adjustment under the present configuration.

Overall, the results support the proposed architecture as an integrated closed-loop mechanism in which synchronized system representation, future-state prediction, risk assessment, orchestration, and feedback updating jointly improve risk-sensitive resource decisions under dynamic disturbances.

6.Discussion, implications, and limitations

6.1.Interpretation of the main findings

The simulation results presented in Chapter 5 provide evidence that the proposed closed-loop risk-aware orchestration approach can improve several operational performance dimensions relative to static allocation, predictive allocation, and risk-aware orchestration. Among the four evaluated strategies, the proposed approach achieves the highest system utility and the lowest shortage, constraint-violation, and aggregate risk values. These improvements are accompanied by higher resource deployment cost, indicating that enhanced operational protection requires additional resource expenditure.

The comparative results also reveal a progressive relationship among prediction, risk assessment, and closed-loop decision updating. Static Allocation does not explicitly incorporate future-state information or dynamic risk conditions. Predictive Allocation introduces future-state information and produces improvements in utility, shortage, constraint violation, and risk relative to static allocation. Risk-Aware Orchestration further incorporates risk into the decision objective and achieves additional improvements in risk-related outcomes. The proposed strategy extends this process by introducing digital-twin synchronization, feedback correction, and dynamic risk-weight adjustment.

The comparison between the proposed strategy and Risk-Aware Orchestration is particularly important because it isolates the incremental contribution of the closed-loop mechanism. The proposed strategy improves utility by approximately 2.34%, reduces shortage by approximately 2.04%, reduces constraint violation by approximately 3.69%, and reduces aggregate risk by approximately 2.39% relative to Risk-Aware Orchestration. Although these improvements are moderate, they indicate that the proposed contribution is not limited to adding prediction or a risk penalty to an allocation model. Instead, the results suggest that continual coordination between predicted conditions, realized system responses, and subsequent decision updates can provide additional operational benefits.

The cost results provide an important qualification. The proposed strategy incurs approximately 5.52% higher cost than Risk-Aware Orchestration. Therefore, the proposed approach should not be interpreted as a universally cost-minimizing strategy. Its objective is to balance utility, resource expenditure, and operational risk, with greater resource deployment being accepted when it contributes to lower shortage, fewer constraint violations, and reduced risk exposure.

The volatility results also require a cautious interpretation. The proposed strategy produces a volatility value close to that of Risk-Aware Orchestration, and the corresponding Wilcoxon signed-rank test does not indicate a statistically significant difference. Consequently, the current results support improvements in utility, shortage, constraint violation, and aggregate risk, but they do not establish a clear volatility-reduction advantage.

The ablation results provide additional insight into the internal mechanism of the framework. Removing twin synchronization increases shortage, constraint violation, and risk relative to the full ablation configuration. Removing feedback correction produces a more visible deterioration in utility and risk-related outcomes, suggesting that feedback correction is an important component of the closed-loop decision process. By contrast, the difference between the fixed-risk-weight and full variants is comparatively small. This indicates that dynamic risk-weight adjustment provides a modest incremental benefit under the present simulation configuration, whereas the more substantial contribution is associated with the integrated synchronization–feedback mechanism.

6.2.Theoretical and methodological implications

The principal theoretical implication of the proposed framework is that predictive risk assessment is positioned as a decision-transition mechanism between future-state prediction and resource orchestration. In a conventional predictive decision system, a predictive model generates an estimate of future conditions, while a separate optimization procedure determines an action based on a predefined objective. In the proposed framework, predicted future conditions are not treated merely as additional descriptive information. They are translated into a risk representation that directly influences the orchestration decision.

The decision relationship can be expressed using the objective already established in the methodological formulation:

$$J_t(u_t)=U_t(u_t)-\alpha C_t(u_t)-\beta_t r_t(u_t) \tag{32}$$

In this formulation, $U_t(u_t)$ represents the utility associated with a decision, $C_t(u_t)$ represents its resource cost, and $r_t(u_t)$ represents the decision-dependent risk term. The dynamic risk weight β_t determines the relative importance assigned to risk under the prevailing system conditions. The significance of this formulation is not the inclusion of a risk penalty alone, since risk-sensitive objectives are already established in

decision and optimization research. Rather, the proposed framework emphasizes how predicted future conditions are converted into risk information and subsequently incorporated into a continuously updated orchestration process.

This perspective provides a more specific interpretation of the framework's novelty. The contribution is not the independent invention of artificial intelligence, digital twins, prediction, risk assessment, optimization, or feedback control. Each of these components has been extensively studied. The contribution lies in specifying their functional relationship, particularly the role of predictive risk assessment as the transition between future-state intelligence and resource orchestration, and in connecting this relationship to digital-twin synchronization and feedback correction.

The framework also provides a more structured interpretation of closed-loop decision-making. The digital twin is not treated merely as a visualization layer or a passive digital representation. It serves as an intermediate state representation through which observed system conditions, predicted future states, realized responses, and subsequent corrections can be related. This makes the digital twin relevant to the decision process rather than limiting its function to monitoring or simulation.

Feedback is similarly interpreted as more than a post-decision reporting mechanism. It provides information about the discrepancy between predicted and realized system states and supports the revision of the digital-twin representation and subsequent orchestration decisions. The ablation results are consistent with this interpretation, since removing feedback correction weakens utility and increases several adverse operational outcomes.

The findings also clarify the meaning of resource orchestration in this study. Resource orchestration is defined as the repeated coordination, prioritization, allocation, adjustment, and reallocation of resources in response to predicted system evolution, operational risk, realized outcomes, and system constraints. It therefore extends beyond static allocation and differs from dynamic allocation in its explicit emphasis on coordination among multiple objectives, risk conditions, constraints, and feedback-driven policy revision.

Under this interpretation, the distinction among the evaluated strategies is not merely temporal. Static Allocation assigns resources according to fixed conditions. Predictive Allocation adjusts decisions using future-state information. Risk-Aware Orchestration incorporates risk into the decision objective. Closed-Loop Risk-Aware Orchestration additionally uses synchronized system representations and realized feedback to revise subsequent decisions. This distinction provides a more precise basis for discussing orchestration as a decision process rather than as a synonym for repeated allocation.

6.3.Domain adaptability and practical implications

The proposed framework is designed around a set of functional components that can be adapted to different complex-system environments. These components include system-state representation, digital-twin synchronization, future-state prediction, dynamic risk assessment, resource orchestration, system-response observation, and feedback updating. Their generality, however, should be understood as functional adaptability rather than complete domain independence.

Different application domains require different state variables, resource definitions, risk structures, temporal scales, data sources, and operational constraints. For example, a manufacturing system may represent machine conditions, production queues, energy consumption, and maintenance requirements. An energy system may involve demand, supply, storage, transmission capacity, and price volatility. A transportation network may include traffic density, travel time, vehicle availability, and infrastructure constraints. A financial network may involve liquidity, exposure, market volatility, and inter-institutional dependencies.

The overall logic of the framework can remain consistent across these settings, but the specific implementation must be domain-dependent. In particular, the risk term $r_t(u_t)$, the state-transition representation, the prediction target, the feasible decision set, and the evaluation metrics must be defined according to the characteristics of the target system. Consequently, the framework should be regarded as domain-adaptable rather than directly transferable without modification.

The practical relevance of the framework is therefore conditional on the availability of sufficiently reliable observations, an adequate digital-twin representation, a predictive model appropriate to the system structure, and a decision mechanism capable of operating within the available computational and temporal constraints. The framework is most relevant to systems in which current decisions affect future system conditions and where resource shortages, constraint violations, or adverse operational states have meaningful consequences.

The results also illustrate that risk-aware orchestration involves an explicit trade-off between protection and expenditure. A strategy that reduces shortage and risk may require additional resource deployment. In practical applications, the appropriate balance should therefore be determined by the operational priorities, risk tolerance, and resource limitations of the target system. The objective is not to eliminate all risk or minimize cost in isolation, but to support more informed and adaptive trade-offs among competing objectives.

From a computational perspective, the present validation uses a compact MLP predictor with a 12-dimensional input and hidden layers of 48 and 24 units. This design provides a relatively manageable predictive component for repeated inference within the simulated decision cycles. However, the computational requirements of a practical implementation will depend on the dimensionality of the system state, the number of resource variables, the frequency of synchronization, the complexity of the optimization problem, and the architecture selected for prediction. More complex graph-based, recurrent, or multimodal models may be appropriate for particular domains, but they may also introduce additional computational and communication costs.

Therefore, real-time applicability should not be evaluated only in terms of prediction accuracy. It should also be assessed in terms of synchronization latency, inference time,

optimization time, communication overhead, update frequency, and the ability to maintain feasible decisions under changing constraints.

6.4.Limitations and future research

Several limitations define the scope of the present findings.

First, the validation is conducted in a controlled synthetic simulation environment rather than through real-world deployment or a field case study. This design makes it possible to compare the four strategies and examine the contribution of individual components under controlled conditions. However, real systems may involve incomplete observations, irregular sampling, sensing delays, communication failures, heterogeneous data quality, organizational restrictions, and unexpected disturbances that are not fully represented in the current simulation.

Second, the predictive module is instantiated as a compact MLP. Although this implementation supports transparency and computational manageability, it does not establish that the same decision mechanism would perform equally well with graph-based, recurrent, attention-based, or multimodal architectures. The current results should therefore be interpreted primarily as evidence for the proposed decision structure rather than as evidence that the selected MLP architecture is universally optimal.

Third, the mathematical risk term $r_t(u_t)$ is operationalized in the simulation through a normalized aggregate risk measure. This provides a practical way to compare the strategies, but real-world risk may involve more complex characteristics, including rare but severe events, correlated uncertainty, cascading failures, asymmetric losses, and tail exposure. Future research should examine probabilistic, scenario-based, distributionally robust, or tail-sensitive risk representations where these features are important.

Fourth, the present study does not provide formal convergence, stability, or long-term optimality guarantees. The feedback mechanism offers a structure for continual correction, but it does not establish that repeated updates will always converge to a stable policy or improve performance under every disturbance pattern. Formal analysis would require additional assumptions concerning system dynamics, prediction errors, synchronization accuracy, update rules, objective properties, and constraint feasibility.

Fifth, the current evaluation does not fully examine severe distribution shifts, abrupt structural changes, prolonged degradation, or adversarial disturbances. Under such conditions, the predictive model may become inaccurate, and ordinary feedback correction may not be sufficient. The digital twin may require recalibration, structural updating, or a change in the predictive model itself. Future research should therefore examine shock-phase behavior, recovery dynamics, and post-shock adaptation separately from aggregate performance across decision cycles.

Sixth, closed-loop orchestration may increase computational and communication overhead because it requires repeated synchronization, prediction, risk assessment, optimization, and feedback updating. This overhead may become substantial in high-dimensional, graph-structured, multi-agent, or high-frequency systems. Future studies should evaluate the relationship among synchronization frequency, prediction accuracy, optimization time, resource expenditure, and decision quality.

Seventh, the current formulation represents utility, cost, and risk within a unified decision structure but does not explicitly model multiple stakeholders with conflicting preferences or different risk tolerances. Real-world socio-technical systems may require fairness constraints, preference aggregation, decentralized coordination, accountability mechanisms, privacy protection, or human oversight. These issues are important extensions for future research.

Future work should therefore proceed in several directions. Real-world or semi-real-world datasets can be used to examine the effects of incomplete observations, data latency, model mismatch, and operational constraints. Alternative predictive architectures can be evaluated according to the structural properties of the target domain rather than selected solely for technical complexity. Risk modeling can be expanded to include probabilistic failure, scenario-based exposure, cascading risk, distributional uncertainty, and tail-sensitive objectives.

Further research should also develop formal analyses of synchronization error, prediction error propagation, feedback stability, and constraint feasibility. Experiments involving explicit shock and recovery phases would provide a more direct assessment of adaptive response, while larger-scale simulations could evaluate computational scalability under more complex state spaces, resource types, and decision frequencies. Finally, multi-agent and stakeholder-aware extensions may improve the framework's applicability to distributed socio-technical systems.

6.5.Concluding discussion

The proposed framework provides a structured approach for connecting digital-twin synchronization, future-state prediction, dynamic risk assessment, resource orchestration, and feedback correction. The simulation results indicate that the proposed closed-loop strategy achieves more favorable utility, shortage, constraint-violation, and aggregate-risk outcomes than the evaluated baseline strategies, although these gains are accompanied by higher resource deployment cost. The volatility results do not show a statistically significant improvement relative to Risk-Aware Orchestration.

The ablation findings further suggest that the principal incremental contribution is associated with the integrated synchronization – feedback mechanism, while dynamic risk-weight adjustment provides a smaller additional benefit under the present experimental configuration. These findings support the interpretation that the framework's value lies in the interaction among its components rather than in the isolated addition of a predictive model, a risk penalty, or a feedback loop.

At the same time, the framework should not be interpreted as providing universal convergence, stability, risk elimination, or domain-independent performance guarantees. Its effectiveness depends on the quality of system observations, the fidelity of digital-twin synchronization, the adequacy of prediction, the definition of the risk function, the feasibility of orchestration decisions, and the computational resources

available for repeated updating. The present study therefore offers a theoretically grounded and simulation-supported approach whose broader applicability requires further domain-specific validation, scalability analysis, and formal investigation.

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Declarations

Conflict of interest The author declares no conflict of interest.

References

[1] WATTS D J, STROGATZ S H. Collective dynamics of 'small-world' networks. Nature, 1998, 393: 440-442.
[2] BARABÁSI A L, ALBERT R. Emergence of scaling in random networks. Science, 1999, 286(5439): 509-512.
[3] EISENBERG L, NOE T H. Systemic risk in financial systems. Management Science, 2001, 47(2): 236-249.
[4] MAY R M, ARINAMINPATHY N. Systemic risk: The dynamics of model banking systems. Nature, 2010, 468: 324-327.
[5] GAI P, KAPADIA S. Contagion in financial networks. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2010, 466(2120): 2401-2423.
[6] HALDANE A G, MAY R M. Systemic risk in banking ecosystems. Nature, 2011, 469: 351-355.
[7] ELLIOTT M, GOLUB B, JACKSON M O. Financial networks and contagion. American Economic Review, 2014, 104(10): 3115-3153.
[8] ACEMOGLU D, OZDAGLAR A, TAHBAZ-SALEHI A. Systemic risk and stability in financial networks. American Economic Review, 2015, 105(2): 564-608.
[9] GLASSERMAN P, YOUNG H P. Contagion in financial networks. Annual Review of Economics, 2016, 8: 201-229.
[10] LEE J, BAGHERI B, KAO H A. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 2015, 3: 18-23.
[11] KRITZINGER W, KARNER M, TRAAR G, et al. Digital twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 2018, 51(11): 1016-1022.
[12] TAO F, ZHANG H, LIU A, et al. Digital twin and its potential application in industry. CIRP Annals, 2019, 68(1): 167-170.
[13] BARRICELLI B R, CASIRAGHI E, FOGLI D. A survey on digital twin: Definitions, characteristics, applications, and design implications. IEEE Access, 2019, 7: 167653-167671.
[14] JONES D, SNIDER C, NASSEHI A, et al. Characterising the digital twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology, 2020, 29: 36-52.
[15] FULLER A, FAN Z, DAY C, et al. Digital twin: Enabling technologies, challenges and open research. IEEE Access, 2020, 8: 108952-108971.
[16] RASHEED A, SAN O, KVAMSDAL T. Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access, 2020, 8: 21980-22012.
[17] HUANG Z, SHEN Y, LI J, et al. A survey on AI-driven digital twins in Industry 4.0: Smart manufacturing and advanced robotics. Sensors, 2021, 21(19): 6340.
[18] WANG G, ZHANG G, GUO X, et al. Digital twin-driven service model and optimal allocation of manufacturing resources in shared manufacturing. Journal of Manufacturing Systems, 2021, 59: 165-179.
[19] ZHAO Z, ZHANG M, CHEN J, et al. Digital twin-enabled dynamic spatial-temporal knowledge graph for production logistics resource allocation. Computers & Industrial Engineering, 2022, 171: 108454.
[20] HAN J, CHEN Z, HU P, et al. Digital twin power grid oriented mobile edge network resource allocation model. IEEJ Transactions on Electrical and Electronic Engineering, 2023, 18(10): 1682-1693.
[21] SCHENA L, MARQUES P A, POLETTI R, et al. Reinforcement twinning: From digital twins to model-based reinforcement learning. Journal of Computational Science, 2024, 82: 102421.
[22] SHAO G, HIGHTOWER J, SCHINDEL W. Credibility consideration for digital twins in manufacturing. Manufacturing Letters, 2023, 35: 24-28.