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Operational Digital Twins in the Loop: Toward Symbiotic Intelligence for Industrial Systems

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***Abstract*—Digital twins (DTs) are increasingly recognized as a foundational infrastructure for cyber–physical intelligence in industrial systems. In this work, the term operational DTs in the loop refers to DTs embedded in recurrent cycles of sensing, state synchronization, prediction, decision-making, actuation, and experience-driven updating. Existing studies often treat DTs as lifecycle management tools or isolated modeling technologies but lack a unified system-level explanation of how DT capabilities are embedded in operational closed loops. This work reconceptualizes industrial DTs as lifecycle-spanning intelligent systems grounded in bidirectional virtual–physical coupling. We introduce a conceptual framework that integrates lifecycle stages with the evolution of virtual–physical relationships, organized into five capability levels: virtual emulation, real-time mapping, executable control, anticipatory prediction, and operational symbiosis. Focusing on the operational stage, we analyze how DTs evolve from analytical representations toward observable, executable, anticipatory, and increasingly coordinated systems, and how operational feedback informs design refinement, predictive maintenance, and lifecycle knowledge evolution. We then outline systemic challenges toward higher level closed-loop intelligence, including interaction interfaces, data governance and open benchmarking, trustworthy decision-making, sustainable optimization, and human-centric collaboration. On this basis, we provide a roadmap for trustworthy, sustainable, and human-centric operational intelligence.**

***Index Terms*—Cyber–physical intelligence, operational digital twins (DTs), symbiotic intelligence, virtual–physical interaction.**

Received 22 May 2026; revised 31 August 2026 and 5 October 2026; accepted 16 October 2026. This work was supported in part by the National Key Research and Development Program of China under Grant 2025YFE0203700, in part by the Fundo para o Desenvolvimento das Ciencias e da Tecnologia under Grant 0095/2025/AMJ, in part by Beijing Natural Science Foundation under Grant L233005, and in part by the National Natural Science Foundation of China under Grant 62473014. *(Corresponding author: Jing Bi.)*

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Color versions of one or more figures in this article are available at https://doi.org/10.1109/TSMC.2026.3745387.

Digital Object Identifier 10.1109/TSMC.2026.3745387

NOMENCLATURE

$\mathbf{x}_t$	True physical state at time t.
$\tilde{\mathbf{x}}_t$	Emulated or simulated state in the virtual twin.
$\hat{\mathbf{x}}_t$	Estimated current state from real-time observations.
$\hat{\mathbf{x}}_{t+\tau\|t}$	Predicted future state at horizon τ given information up to t.
$\mathbf{x}_k^{\text{ref}}$	Reference state or trajectory.
$\mathbf{y}_t$	Observable output or measurement at time t.
$\mathbf{u}_t$	Control input/executable action at time t.
$\mathbf{u}_t^{(i)}$	Control action of subsystem i at time t.
$\mathbf{z}_t$	Discrete operational decision variable.
$\mathbf{w}_t$	Exogenous disturbance at time t.
$\mathbf{v}_t$	Measurement noise at time t.
$\hat{q}_{t+\tau\|t}$	Predicted outcome, e.g., quality, defect score, or failure risk.
e_t	Residual/deviation indicator for anomaly detection at time t.
$f(\cdot)$	Physical state-transition dynamics.
$\hat{f}(\cdot)$	Approximate twin/predictive dynamics model.
$f^{(i)}(\cdot)$	State-evolution model of subsystem i.
$\phi^{(i)}(\cdot)$	Cross-entity coupling/interaction function of subsystem i.
$h(\cdot)$	Observation function from latent state to output.
$h_{\boldsymbol{\theta}}(\cdot)$	Parameterized observation model.
$g_\tau(\cdot)$	State-evolution predictor over horizon τ.
$\psi_\tau(\cdot)$	Outcome-oriented predictor over horizon τ.
$\pi_\theta(\cdot)$	Parameterized control policy.
$\pi^{(i)}(\cdot)$	Control/coordination policy of subsystem i.
$J(\pi)$	Expected cumulative objective for offline policy evaluation.
$\ell(\cdot)$	Stage cost function.
K_t	Estimator gain.
$\mathcal{R}(\mathbf{x})$	Regularization/prior term in state estimation.
$\mathbf{c}_{\text{opt}}$	Cost vector in combinatorial optimization.
$\mathcal{N}(i)$	Neighbor set of subsystem/entity i.
$\mathbf{c}_t$	Shared operational context at time t.

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$\mathcal{D}_t$	Experience log/accumulated operational data up to time t.
$\mathcal{M}(\cdot)$	Policy update operator.

I. Introduction

MODERN industrial systems are evolving into large-scale cyber–physical ecosystems characterized by heterogeneous assets, dynamic uncertainty, and tightly coupled interactions between physical processes and computational intelligence [1]. As production and process systems become more data-driven and autonomous, the traditional separation among modeling, monitoring, prediction, and control is no longer sufficient to ensure efficiency, resilience, and sustainability. Next-generation industrial intelligence requires recurrent feedback between physical operations and their digital representations, enabling systems to perceive, decide, act, and adapt in real time [2]. Within this paradigm shift, digital twins (DTs) have emerged as a promising architectural foundation for operational intelligence in industrial systems.

Despite the rapid growth of research on industrial DTs, existing surveys often organize the field from lifecycle-oriented [3], [4], technology-centric [5], application-oriented, or bibliometric perspectives. Lifecycle-oriented studies emphasize data continuity across design, operation, and maintenance [6]; technology-centric studies focus on enabling technologies and methods, including Internet of Things (IoT) infrastructures [7], simulation models [8], artificial intelligence algorithms [9], and edge-cloud architectures [10]; application-oriented surveys summarize domain-specific deployments; and bibliometric analyses characterize publication trends and knowledge structures. These studies clarify where DTs are applied, which technologies enable their implementation, and how information is integrated across lifecycle stages. However, existing surveys lack a unified system-level account of how heterogeneous DT capabilities become embedded in operational loops of perception, state synchronization, prediction, decision-making, actuation, and experience-driven updating. Therefore, it remains unclear how deeper virtual–physical coupling transforms a DT from an offline analytical model into a real-time observer, an executable decision component, an anticipatory mechanism, and a participant in coordinated system adaptation.

In this review, the term operational DTs in the loop refers to DTs embedded in recurrent cycles of sensing, state synchronization, prediction, decision-making, actuation, and experience-driven updating. The phrase "in the loop" is used in a systems sense rather than as a narrow hardware-in-the-loop configuration: a twin becomes increasingly in the loop when its virtual states, predictive models, or decision outputs actively participate in real-time operational feedback. This review considers operational DTs in industrial systems, with primary emphasis on intelligent manufacturing and process industries. Representative settings include discrete production environments, such as automotive assembly, electronics manufacturing, and semiconductor fabrication, as well as process industries [11], such as chemical processing, steel production, and oil refining.

Table I summarizes the analytical orientations and highlights the unresolved need for a unified explanation of how DT capabilities are progressively embedded in operational closed loops. To address this gap, this review reconceptualizes industrial DTs through the lens of virtual–physical relationship evolution and layered closed-loop intelligence. We use closed-loop intelligence as the evaluative criterion for assessing the degree to which an operational DT integrates perception, decision-making, execution, feedback, and learning. Under this criterion, symbiotic intelligence does not merely denote higher automation; rather, it refers to a regime in which physical processes, virtual models, decision policies, human operators, and lifecycle knowledge become mutually coupled, continuously updated, and jointly adaptive across operational loops. The operational stage is taken as the analytical anchor because it is where sensing, decision-making, and actuation physically converge, while design and maintenance remain essential lifecycle contexts that shape and are reshaped by operational intelligence. Therefore, design and maintenance-related studies are included when their models, information, or feedback directly support operational decision-making or are updated through operational experience. The main contributions of this review are summarized as follows.

1) A system-level framing of operational DTs in the loop that takes operation as the analytical anchor and examines how DTs participate in recurrent virtual–physical feedback across the industrial lifecycle.
2) A five-level analytical framework of virtual–physical relationship evolution, spanning virtual emulation, virtual–physical mapping, control, prediction, and operational symbiosis, with closed-loop intelligence adopted as the criterion for interpreting capability development.
3) A lifecycle-oriented capability matrix that organizes DT capabilities across lifecycle stages and levels of virtual–physical coupling, together with a roadmap that synthesizes cross-lifecycle implications and key challenges toward trustworthy and human-centric operational intelligence.

The remainder of this article is organized as follows (Fig. 1). Section II introduces the conceptual framework and evaluation criteria, including the lifecycle perspective, virtual–physical relationship evolution, and a taxonomy of operational DT capabilities. Section III focuses on operational DTs, analyzing the progressive deepening of closed-loop intelligence from virtual emulation to operational symbiosis. Section IV discusses cross-lifecycle implications. Section V examines open challenges and promising directions toward human-centric and sustainable operational DTs. Finally, Section VI concludes this article.

II. Conceptual Framework and Evaluation Criteria

A. Lifecycle Perspective

Industrial DTs operate across lifecycle stages, including design, operation [15], and maintenance [16]. These stages are often discussed separately. However, they are closely connected in cyber–physical systems. The design stage defines

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TABLE I

COMPARISON OF REPRESENTATIVE DT SURVEY ORIENTATIONS AND THEIR TREATMENT OF OPERATIONAL CLOSED-LOOP INTELLIGENCE

Orientation	Primary Focus	View of Digital Twin	Closed-Loop Perspective
Lifecycle-Oriented Surveys [3], [4]	Integration across design, production, operation, and maintenance	Lifecycle information carrier and cross-stage information integration	Operational perception, decision, and actuation mechanisms remain largely implicit
Technology-Centric Surveys [5], [11]	Enabling infrastructures, models, and computational methods for DT implementation and integration	Technology stack combining sensing, modeling, analytics, and edge-cloud services	Individual components and algorithms are discussed without a unified account of how they form executable operational loops
Application and Industry-Oriented Surveys [12]	Sector-specific DT applications, deployment patterns, and operational problem solving	Domain-oriented solution frameworks tailored to specific industrial processes and tasks	Closed-loop capabilities are described through individual implementations but lack a cross-domain capability structure
Scientometric and Bibliometric Surveys [13], [14]	Publication patterns, research trends, and knowledge networks	Research landscape reflecting the development of the DT field	Functional mechanisms and operational capability evolution are not explicitly analyzed
Operational Closed-Loop Perspective (This Review)	Virtual-physical relationship evolution and capability development within a lifecycle structure	An evolving cyber-physical intelligence system embedded in operational feedback loops	Closed-loop intelligence is analyzed as cumulative capabilities in observability, execution, anticipation, and experience-driven adaptation

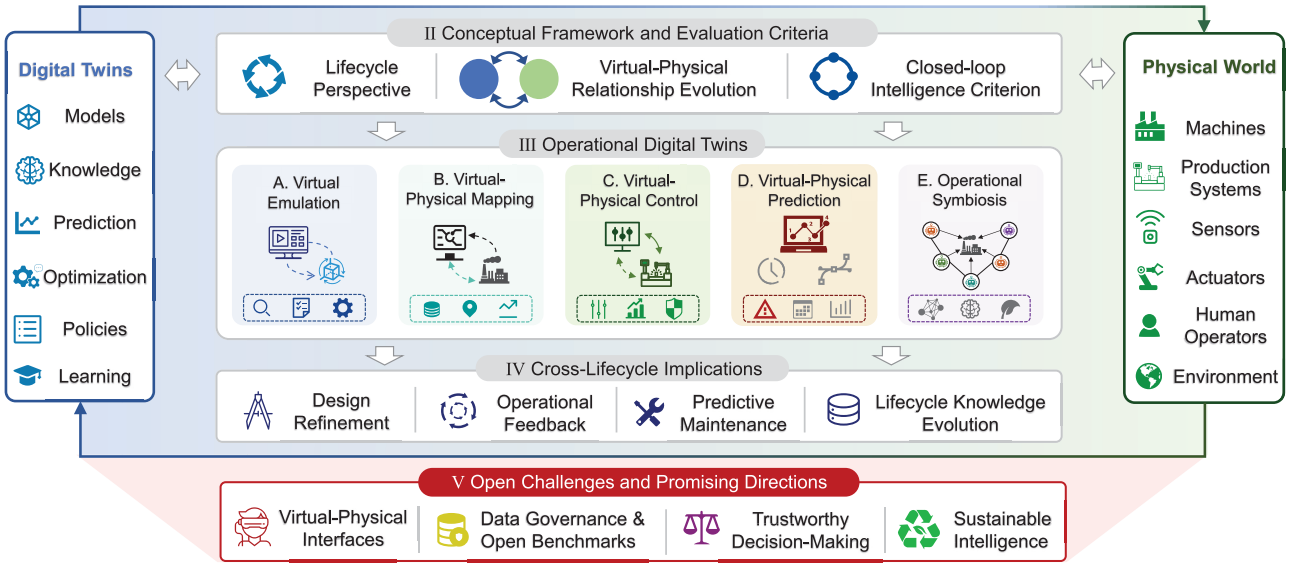

Fig. 1. Structure of this article. The review progresses from lifecycle-oriented conceptual foundations and capability taxonomy to operational DT evolution, cross-lifecycle implications, and open challenges toward higher level closed-loop intelligence.

system structures, models, and key parameters. The operation stage incorporates sensing, decision-making, control, and adaptation. The maintenance stage supports system reliability and long-term performance. A separate treatment of these stages overlooks important feedback between them. Operational data can update design assumptions, while maintenance results can guide later operational strategies [6]. From a systems perspective, lifecycle integration therefore involves more than continuous information exchange. It also provides the structural basis for closed-loop intelligence [17]. Design models can support decisions during operation, and maintenance analytics can improve long-term reliability. At the same time, operational environments continuously generate large volumes of operational experience data. These data can further refine design parameters, maintenance policies, and lifecycle knowledge.

Therefore, this review uses a lifecycle perspective to place DT evolution in a broader context while maintaining a complete lifecycle view and emphasizing the operational stage. Operation provides the main setting in which closed-loop intelligence is realized in physical systems. In this stage, sensing, decision-making, and actuation interact through real-time feedback. Design provides the models, constraints, and reference configurations required for operation. Maintenance uses operational feedback to support long-term reliability. Operation therefore acts as the main analytical link among these lifecycle stages because it enables executable feedback. At the same time, design and maintenance remain essential parts of the lifecycle. Their models and decisions shape operational intelligence while being continuously refined through feedback from real-world operational evidence.

B. Virtual–Physical Relationship Evolution

Beyond lifecycle staging, the maturation of industrial DTs can be interpreted through virtual–physical relationship evolution [18]. At its core, a DT embodies bidirectional coupling between physical systems and digital representations. The

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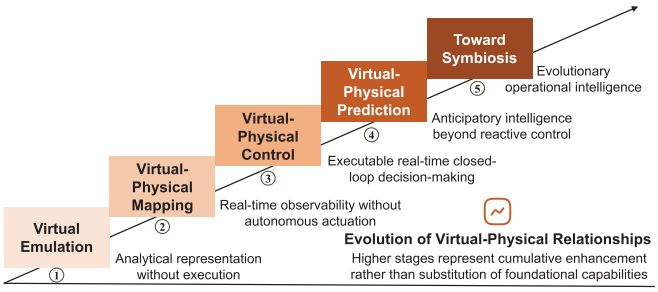

Fig. 2. Capability levels of closed-loop intelligence across virtual–physical relationship evolution. The capability levels range from offline analytical support to real-time observability, executable control, predictive intelligence, and higher order symbiotic intelligence.

depth and structure of this coupling determine whether the twin becomes "in the loop," i.e., whether its virtual states, predictive models, or decision outputs participate in operational feedback. Instead of classifying DTs by application tasks such as monitoring, diagnosis, optimization, or maintenance, we distinguish five capability levels according to how virtual representations participate in physical operation: analytical representation, state synchronization, executable intervention, anticipatory inference, and system-level adaptation. These task-oriented functions appear at multiple capability levels depending on how they are embedded in the operational loop. As illustrated in Fig. 2, the relationship between virtual and physical systems gradually evolves from virtual emulation to operational symbiosis.

1) Virtual emulation [19] builds a digital representation of the physical system without directly affecting its operation. It supports offline validation and exploration of different scenarios.
2) Virtual–physical mapping [20] enables real-time synchronization between virtual and physical states. It establishes a basic perceptual feedback loop.
3) Virtual–physical control [21] introduces executable decisions into the interaction process. It closes an operational loop by connecting decision-making with physical systems.
4) Virtual–physical prediction [22] extends the system beyond reactive adjustment. It supports anticipatory planning and enables intervention based on predicted risks.
5) Operational symbiosis reflects an emerging higher order capability. It enables coordination across systems, adapts to changing contexts, and evolves through accumulated experience.

These five levels describe distinct capability configurations and do not constitute a mandatory sequential path. Industrial DTs may combine capabilities from different levels, such as mapping with prediction without autonomous control, or executable control without system-level symbiosis. Higher capability levels therefore do not replace earlier ones or represent a universally preferable design target. The appropriate level depends on application requirements, safety constraints, regulatory conditions, and the desired degree of human supervision. Analytical modeling remains indispensable for validation and robustness, even in highly autonomous systems. Thus, virtual–physical evolution is viewed as a cumulative yet configurable enhancement of capabilities, characterized by increasing interaction depth, expanding feedback horizons, and stronger DT participation in operational loops, from offline analysis to real-time control and long-term adaptation. Accordingly, closed-loop intelligence provides a conceptual basis for interpreting how deeply DT capabilities are embedded in operational feedback.

C. Taxonomy of Operational DT Capabilities

To integrate the lifecycle perspective with virtual–physical relationship evolution, Fig. 3 presents a capability matrix of industrial DTs. The vertical axis shows the lifecycle stages, including design, production/operation, and maintenance. The horizontal axis describes how virtual–physical interaction develops from virtual emulation to operational symbiosis. Each cell summarizes the capabilities supported by a specific coupling mode at a given lifecycle stage. The matrix provides both a taxonomy and a qualitative basis for comparing DT capabilities across different lifecycle stages and levels of virtual–physical interaction.

Consistent with Section I, *closed-loop intelligence* is adopted as the conceptual evaluative criterion for interpreting DT capabilities. Virtual emulation provides analytical support without executable feedback; mapping establishes real-time observability; control introduces executable actuation; prediction enables anticipatory decision-making; and symbiosis reflects cross-system coordination and experience-driven adaptation. The five capability levels differ in how these dimensions are instantiated and combined within operational loops. This review centers on the production/operation stage (highlighted in Fig. 3). This emphasis reflects the fact that closed-loop intelligence becomes physically executable most directly during system operation, where sensing, decision-making, and actuation converge [23], [24], [25], [26]. Design and maintenance provide modeling and predictive foundations, yet operational environments are where DTs evolve from analytical representations into adaptive and potentially autonomous systems. The taxonomy integrates lifecycle structure with virtual–physical capability evolution and uses closed-loop intelligence as an evaluative basis for comparing capability configurations across lifecycle contexts.

III. Operational DTs: From Emulation to Symbiotic Intelligence

Operational DTs exhibit different capability configurations as virtual emulation, mapping, control, and prediction are incorporated into operational feedback loops. These capability levels describe the functional role of a DT, while techniques such as state estimation, reinforcement learning (RL), and mathematical optimization provide alternative implementation mechanisms. Accordingly, one capability level may be realized by multiple methods, and the same method may support different levels depending on its role in the operational loop. The mathematical formulations in this section are generic abstractions for characterizing and comparing mechanisms

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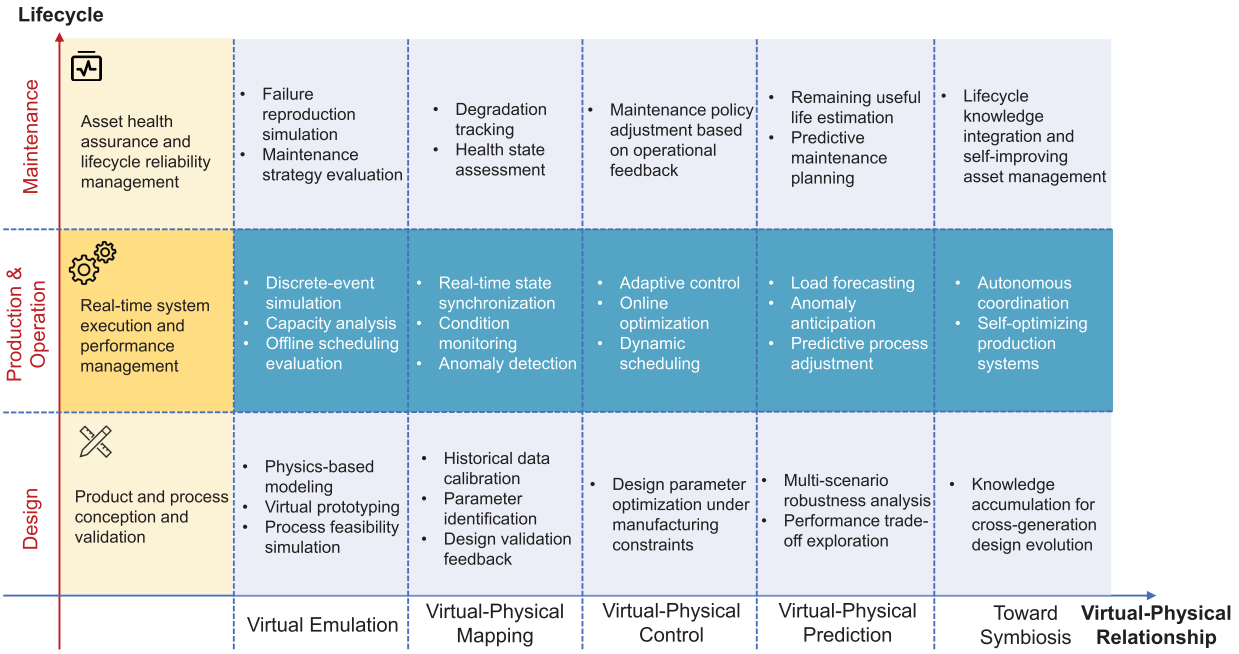

Fig. 3. Lifecycle-oriented capability matrix of industrial DTs across virtual–physical capability levels and lifecycle stages.

reported in the literature. Nomenclature summarizes the main symbols used throughout this article.

A. Virtual Emulation in Operation

Virtual emulation represents the foundational stage of operational DTs, where the physical system is abstracted into a high-fidelity computational model for offline analysis and experimentation [27]. At this stage, the DT functions as an analytical surrogate rather than an executable control entity, providing a sandbox environment for scenario exploration, performance evaluation, and design validation prior to physical deployment.

Formally, let the physical system be described by a state-space model $\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t)$, where $\mathbf{x}_t$ denotes the system state, $\mathbf{u}_t$ denotes the control input, and $\mathbf{w}_t$ denotes the exogenous disturbances. Virtual emulation constructs an approximate model $\hat{f}$ such that $\tilde{\mathbf{x}}_{t+1} = \hat{f}(\tilde{\mathbf{x}}_t, \mathbf{u}_t)$, where $\tilde{\mathbf{x}}_t$ denotes the emulated state in the virtual twin, enabling large-scale simulation of system trajectories without interacting with the physical system. Therefore, decision policies π can be evaluated offline by minimizing expected performance objectives

$$J(\pi) = \mathbb{E}\left[\sum_t \ell(\tilde{\mathbf{x}}_t, \mathbf{u}_t)\right] \tag{1}$$

where $\ell(\cdot)$ denotes the per-step cost function, without incurring real operational risks.

The experimentable DT (EDT) [28] is a key concept in this direction. EDTs extend DTs beyond static representations and treat them as interactive simulation entities. Multiple EDTs can interact within a virtual testbed without direct interaction with the physical system. This setup allows complex industrial scenarios to be tested in a fully virtual environment. It also supports simulation-driven systems engineering, in which system behavior can be examined prior to physical implementation. Recent studies further extend this idea through high-speed and scalable simulation. These simulations allow engineers to validate decisions more efficiently. For example, Fu et al. [29] develop a DT-driven reconfiguration framework for production lines. Their framework evaluates candidate configurations at approximately 400× real-time speed. This accelerated simulation allows the system to examine many alternative configurations under disturbances. It also provides an effective way to explore large combinatorial solution spaces in a virtual environment.

Another line of research focuses on improving model fidelity and reusability. Okachi et al. [30] propose a modular DT modeling method for semiconductor processes. Their method extracts physics-informed intermediate variables to represent dependencies across multiple process stages. These variables also make the resulting models easier to reuse. Lau et al. [31] develop process-aware DTs based on multimodal deep learning. Their approach captures nonlinear relationships between process parameters and fabrication outcomes. Both methods improve the approximation accuracy of $\hat{f}$ and make offline simulation more reliable. Researchers have also used data-driven methods to connect process data with process logic. Process mining is a representative approach. Vitale et al. [32] construct DTs through an offline modeling phase. Their method identifies process models from historical data and then uses fault simulation to perform *what-if* analysis. This allows abnormal operating conditions to be examined systematically without affecting the physical system.

These studies exemplify virtual emulation: DTs reproduce system dynamics, assess decision policies, and test hypothetical scenarios without directly acting on the physical

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system [33]. These capabilities provide the analytical basis for later stages that introduce real-time interaction and executable intelligence. From the perspective of *closed-loop intelligence*, virtual emulation forms a nonexecutable analytical loop. The virtual system supports perception, decision-making, and evaluation. However, it does not provide real-time feedback to control the physical system. Therefore, the loop remains open at the level of physical actuation. Despite this limitation, virtual emulation remains an essential stage because it provides the computational foundation for the capabilities developed at subsequent capability levels.

B. Virtual–Physical Mapping

Virtual–physical mapping enables DTs to synchronize with the physical system in real time. Virtual emulation generates simulated trajectories $\tilde{\mathbf{x}}_t$ using an approximate model $\hat{f}$. On the contrary, virtual–physical mapping estimates the actual system state $\mathbf{x}_t$ from streaming observations and produces an estimated state $\hat{\mathbf{x}}_t$. This transition shifts the main task from forward simulation to inverse inference [34].

Formally, the physical system is characterized by a latent state $\mathbf{x}_t$ and observable outputs $\mathbf{y}_t$: $\mathbf{y}_t = h(\mathbf{x}_t) + \mathbf{v}_t$, where $h(\cdot)$ denotes the observation function and $\mathbf{v}_t$ is the measurement noise. Virtual–physical mapping aims to estimate the hidden state $\mathbf{x}_t$ in real time by solving the following inverse problem:

$$\hat{\mathbf{x}}_t = \arg\min_{\mathbf{x}} \|\mathbf{y}_t - h(\mathbf{x})\|^2 + \mathcal{R}(\mathbf{x}) \tag{2}$$

where $\mathcal{R}(\mathbf{x})$ encodes prior knowledge (e.g., physical constraints or model regularization [35]). Existing approaches to virtual–physical mapping generally fall into three categories.

1) Model-Based State and Parameter Alignment: In this process, DTs continuously adjust their parameters to match observations from the physical system [36]

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_t \|\mathbf{y}_t - h_{\boldsymbol{\theta}}(\hat{\mathbf{x}}_t)\|^2 \tag{3}$$

where $\boldsymbol{\theta}$ denotes the model parameters and $h_{\boldsymbol{\theta}}(\cdot)$ is a parameterized observation model. By continuously reducing the discrepancy between model-predicted and physically observed behavior, parameter alignment preserves the consistency of the virtual model as the physical asset evolves. This supports health monitoring and degradation assessment. For example, Qin et al. [37] develop a DT framework for online battery state-of-health estimation under partial observations, demonstrating state inference from incomplete physical measurements. Song et al. [38] use iterative optimization to track parameter degradation in power electronic systems, illustrating continuous parameter adaptation to asset degradation. In addition, Choksi et al. [39] combine state-space modeling with numerical integration and metaheuristic optimization to align twin dynamics with measured signals in real time.

2) Residual-Driven Deviation and Anomaly Mapping: Another important function of virtual–physical mapping is anomaly detection, which identifies abnormal behavior by analyzing residuals between physical observations and twin predictions: $e_t = \|\mathbf{y}_t - h(\hat{\mathbf{x}}_t)\|$. Large residuals indicate that the physical system has deviated from its expected behavior. De Benedictis et al. [40] apply this idea through an autonomous control loop. The loop monitors and analyzes the state of the system, plans appropriate responses, and executes actions based on shared knowledge. This process allows the system to identify anomalies in industrial IoT environments. Data-driven methods can further improve detection when labeled data is limited. Castellani et al. [41] use DTs to generate synthetic data for weakly supervised anomaly detection. Li et al. [42] develop an end-to-end deep learning architecture with attention mechanisms to support efficient real-time anomaly detection.

3) Hybrid Physics-Learning Latent State Inference: Virtual–physical mapping also allows DTs to estimate latent states or variables that are difficult to measure directly. Hybrid modeling provides an effective way to achieve this goal. Li et al. [43] combine structural DT models with transfer learning to estimate transient responses of wind turbine blades using limited real-world data. Their approach shows that physics-informed knowledge can be combined with data-driven learning to improve system observability when measurements are sparse.

The main difference between these paradigms lies in the way they infer system states from observations. Model-based approaches explicitly align measured outputs with model predictions through optimization. Residual-driven methods mainly identify deviations from expected behavior and do not necessarily reconstruct the complete system state. Hybrid approaches combine physics-based priors with data-driven learning. These approaches can infer latent variables when observations are incomplete or sparse. Table II summarizes this technical taxonomy. It compares the mapping targets, core estimation mechanisms, and main strengths of each paradigm. Overall, virtual–physical mapping transforms DTs into real-time observers of physical systems by solving inverse inference problems, supporting state estimation [44], parameter identification [45], and anomaly detection [42]. From the perspective of *closed-loop intelligence*, virtual–physical mapping establishes the perception loop, where the system becomes continuously observable through real-time data assimilation. However, decision-making and actuation remain external, and thus the loop is not yet closed.

C. Virtual–Physical Control

While virtual–physical mapping establishes the perception loop by estimating system states $\hat{\mathbf{x}}_t$, virtual–physical control completes the loop by generating executable control actions that directly influence the physical system. Control can be expressed as a mapping from estimated states to control inputs: $\mathbf{u}_t = \pi(\hat{\mathbf{x}}_t)$, where $\mathbf{u}_t$ denotes the control action. Unlike mapping, which focuses ON state inference, this stage emphasizes *decision synthesis and actuation*, transforming DTs from passive observers into active decision-making agents. Virtual–physical control can be categorized into three paradigms: model-based optimal control, learning-based policy optimization, and optimization-embedded decision execution. These paradigms differ in how they generate control actions from the current system state.

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TABLE II
TECHNICAL TAXONOMY OF VIRTUAL–PHYSICAL MAPPING APPROACHES IN OPERATIONAL DTS

Technical Category	Mapping Objective	Core Techniques	Technical Strength
Model-based state and parameter alignment	Estimate hidden states or health-related parameters from streaming observations	State estimation [53], parameter identification [54], optimization-based calibration [55]	Strong physical consistency and interpretability; suitable for health monitoring and degradation tracking
Residual-driven deviation and anomaly mapping	Detect deviations between physical observations and twin-predicted behavior	Residual analysis [56], weakly supervised learning [57], attention-based detection [58]	Effective for anomaly awareness and security monitoring under complex operating conditions
Hybrid physics-learning latent state inference	Infer difficult-to-measure states under sparse observations	Physics-informed learning [59], transfer learning [60], multimodal inference [61]	Improved generalization and enhanced observability of latent dynamics

1) Model-Based Optimal Control: It generates control actions by explicitly solving an optimization problem based on the system dynamics. This process can be formulated as a finite-horizon optimal control problem

$$\left\{\mathbf{u}_t^*, \ldots, \mathbf{u}_{t+H-1}^*\right\} = \arg\min_{\{\mathbf{u}_k\}} \sum_{k=t}^{t+H-1} \ell\left(\hat{\mathbf{x}}_k, \mathbf{u}_k\right) \tag{4}$$

$$\text{s.t. } \hat{\mathbf{x}}_{k+1} = \hat{f}\left(\hat{\mathbf{x}}_k, \mathbf{u}_k\right)$$

$$\mathbf{u}_k \in \mathcal{U},\ \hat{\mathbf{x}}_k \in \mathcal{X} \tag{5}$$

where H denotes the prediction horizon.

A representative approach is DT-driven model predictive control (MPC). In this approach, the twin provides accurate state estimates and predictive models for online optimization. Zheng et al. [46] combine a cognitive DT with MPC for real-time control of high-frequency power converters. Their method embeds a mode-driven numerical solver to speed up prediction and meet real-time control requirements. Liu [47] further applies this paradigm to nonlinear systems with time delays. The study introduces a DT-based predictive controller

$$\left\{\mathbf{u}_k^*\right\}_{k=t}^{t+H} = \arg\min_{\{\mathbf{u}_k\}_{k=t}^{t+H}} \sum_{k=t}^{t+H} \left\|\hat{\mathbf{x}}_k - \mathbf{x}_k^{\text{ref}}\right\|^2 + \lambda \|\mathbf{u}_k\|^2 \tag{6}$$

where $\mathbf{x}_k^{\text{ref}}$ denotes the reference trajectory and λ is a regularization parameter. The framework compensates for time delays and adapts the model online. These mechanisms help maintain stable closed-loop control under uncertain conditions. For more complex systems, such as multienergy networks, distributed MPC further extends this approach. It divides the global optimization problem into several coordinated subproblems [48]

$$\min_{\left\{\mathbf{u}_t^{(i)}\right\}} \sum_i \sum_{k=t}^{t+H} \ell^{(i)}\left(\hat{\mathbf{x}}_k^{(i)}, \mathbf{u}_k^{(i)}\right) + \sum_{i,j} \phi^{(i,j)}\left(\mathbf{u}_k^{(i)}, \mathbf{u}_k^{(j)}\right) \tag{7}$$

where coupling terms $\phi^{(i,j)}(\cdot)$ enforce coordination among the decomposed subsystems.

2) Learning-Based Policy Optimization: In contrast to model-based approaches, learning-based methods derive the control policy $\pi(\cdot)$ directly from data, and RL is commonly used to learn such policies. The control objective is to maximize the long-term cumulative reward, i.e.,

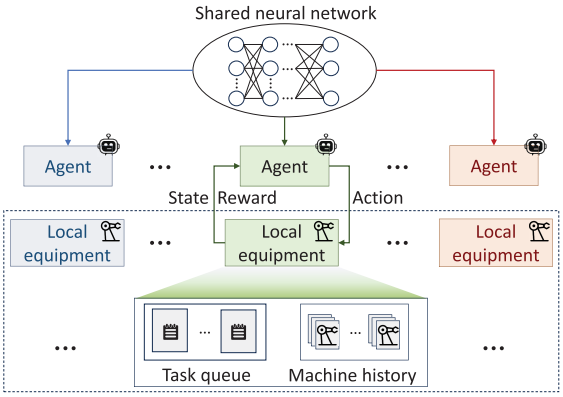

Fig. 4. Agent-oriented RL architecture for learning-based control [49]. Multiple agents interact with the physical environment through state, action, and reward signals, while a shared neural network enables coordinated policy learning.

$$\max_{\pi_\theta} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r\left(\hat{\mathbf{x}}_t, \mathbf{u}_t\right)\right] \tag{8}$$

where π_θ is a parameterized policy, $r(\cdot)$ denotes the reward function, and γ is the discount factor.

In intelligent manufacturing, RL-based DTs are widely used for dynamic scheduling and resource allocation under uncertainty. Park et al. [49] propose an RL framework for semiconductor manufacturing scheduling. In their framework, each agent learns a decentralized policy. The agents also share a global neural network to support coordinated decision-making. The policy is updated as follows:

$$\theta \leftarrow \theta + \alpha \nabla_\theta \mathbb{E}_{\pi_\theta}\left[r_t + \gamma V\left(\hat{\mathbf{x}}_{t+1}\right) - V\left(\hat{\mathbf{x}}_t\right)\right] \tag{9}$$

where $V(\cdot)$ denotes the state-value function and α denotes the learning rate. This update rule allows the control policy to adapt to disturbances such as changes in machine availability and setup conditions [50]. DTs also provide safe and data-rich environments for training and evaluating learning-based control policies. The policies can first be trained in the virtual environment, and real-world feedback can then be used to update them during operation. This process reduces the risks of direct exploration in physical systems and can improve training convergence. Fig. 4 shows a typical agent-oriented

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TABLE III
COMPARISON OF CONTROL SYNTHESIS PARADIGMS FOR VIRTUAL–PHYSICAL CONTROL

Aspect	Model-Based Optimal Control	Learning-Based Policy Optimization	Optimization-Embedded Execution
Control variable	Continuous $\mathbf{u}_t$	Policy $\pi_\theta(\cdot)$	Discrete decision $\mathbf{z}_t$
Control generation	Solve online optimization	Learn policy from data	Solve combinatorial optimization
System model usage	Explicit $f(\cdot)$ required	Implicit (learned from data)	Weak or indirect (constraints)
Temporal structure	Multi-step prediction horizon H	Long-term reward accumulation	Single-step or rolling decision
Adaptivity	Medium (receding horizon)	High (policy updates)	Medium (re-optimization)
Scalability	Limited by optimization complexity	High (once trained)	Limited by combinatorial explosion
Interpretability	High (explicit objective)	Low (black-box policy)	Medium (structured constraints)
Closed-loop intelligence level	Executable and stable control	Adaptive and data-driven control	Operational decision execution
Typical applications	Power systems, process control	Scheduling, resource allocation	Production planning, logistics

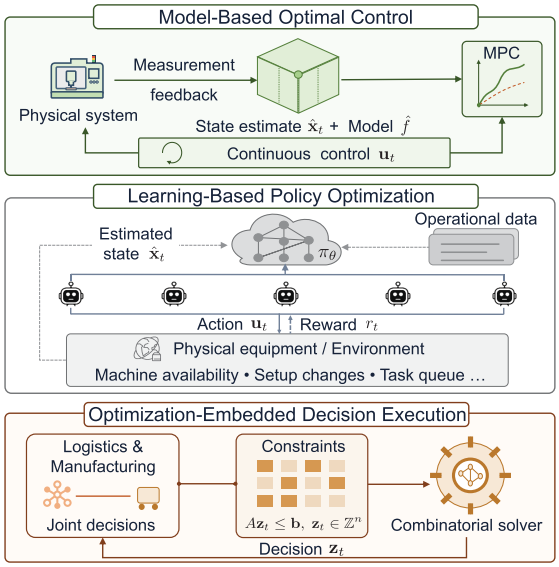

Fig. 5. Representative control synthesis paradigms, illustrating model-based optimal control, learning-based policy optimization, and optimization-embedded decision execution.

RL architecture. Multiple agents interact with the physical environment and learn control policies through shared neural representations.

3) Optimization-Embedded Decision Execution: A third paradigm formulates the control task as a structured optimization problem. Unlike MPC, which emphasizes dynamic system evolution, these methods focus on discrete decision-making under combinatorial constraints. A general formulation can be expressed as

$$\min_{\mathbf{z}_t} \ \mathbf{c}_{\text{opt}}^{\top}\mathbf{z}_t \quad \text{s.t.} \quad A\mathbf{z}_t \le \mathbf{b},\ \mathbf{z}_t \in \mathbb{Z}^n \tag{10}$$

where $\mathbf{c}_{\text{opt}}$ denotes the cost vector, $\mathbf{z}_t$ represents the decision variables, and $(A, \mathbf{b})$ encodes the operational constraints.

In DT-enabled manufacturing systems, structured optimization is often combined with real-time system states. Guo et al. [51] develop a synchronization framework for logistics and manufacturing. Their framework uses system states provided by the DT to jointly optimize logistics and production decisions. This design improves coordination across different production stages. Chang et al. [52] propose a belief-rule-based DT for output control. Their method identifies and optimizes key parameters to obtain the desired system output. Recent studies further combine learning-based surrogate models with combinatorial optimization. This combination reduces the computational cost of solving complex scheduling problems. For example, graph learning can estimate scheduling performance, while metaheuristic optimization guides the search in dynamic job shop environments [62]. Such methods provide efficient decision support for large-scale scheduling problems under uncertainty.

The three paradigms generate control actions through different mechanisms. Model-based methods mainly pursue control optimality and system stability. Learning-based methods provide better adaptability and scalability. Optimization-embedded approaches place greater emphasis on operational constraints and solution feasibility (Fig. 5). Table III illustrates the comparison of these paradigms on control synthesis, model dependence, and operational characteristics. From the perspective of *closed-loop intelligence*, virtual–physical control enables active intervention in physical systems. While mapping provides accurate state estimation, control determines how the system evolves by generating and executing actions in real time. This stage completes the operational closed loop, enabling DTs to understand industrial systems and directly influence their behavior in real time.

D. Virtual–Physical Prediction

If virtual–physical mapping makes the system observable, virtual–physical prediction makes it anticipatory. After the current state has been aligned in the digital space, the next question is no longer what the system is, but what it is likely to become. In this sense, prediction extends operational DTs beyond state synchronization toward forward-looking intelligence, enabling the twin to infer future degradation [63], quality evolution [64], and failure risks [65] before they manifest physically.

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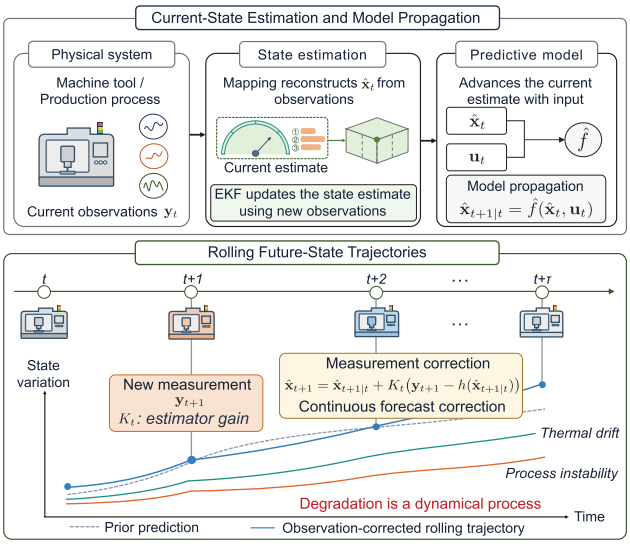

Fig. 6. State-evolution prediction in operational DTs. The current state estimated through virtual–physical mapping is propagated by the predictive model to forecast degradation trajectories, while new measurements continuously correct the prediction.

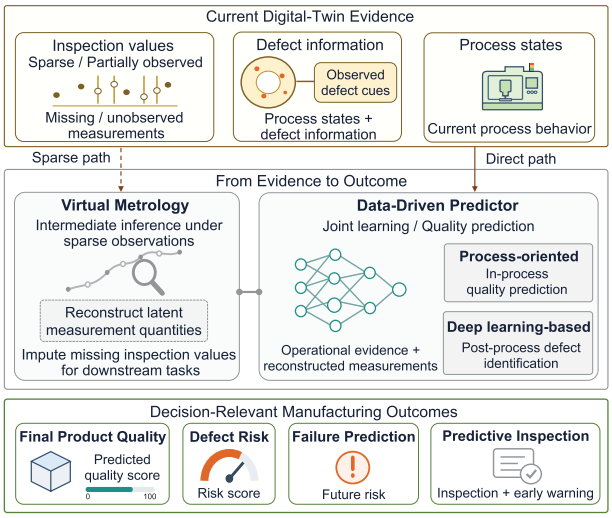

Fig. 7. Outcome-oriented prediction in operational DTs. Virtual metrology reconstructs latent measurements under sparse observations, while data-driven predictors integrate operational evidence and reconstructed information to estimate decision-relevant outcomes such as product quality, defect risk, failure probability, and inspection results.

Prediction seeks to infer a future state or outcome conditioned on the available information up to time t. A general state-evolution prediction problem can be written as

$$\hat{\mathbf{x}}_{t+\tau|t} = g_\tau\left(\hat{\mathbf{x}}_t, \mathbf{u}_{t:t+\tau-1}\right) \tag{11}$$

where $\hat{\mathbf{x}}_{t+\tau|t}$ denotes the predicted state at horizon τ, and $g_\tau(\cdot)$ is the predictive model. In many manufacturing scenarios, the object of interest is not the full future-state trajectory itself, but a task-specific outcome such as defect occurrence, product quality, or failure probability [66]. In that case, the prediction target can be expressed more generally as

$$\hat{q}_{t+\tau|t} = \psi_\tau\left(\hat{\mathbf{x}}_t, \mathbf{y}_{0:t}\right) \tag{12}$$

where $\psi_\tau(\cdot)$ denotes an outcome prediction function over the horizon τ, and $\hat{q}_{t+\tau|t}$ represents a specific prediction target (e.g., a quality index, defect score, or failure risk).

We group existing virtual–physical prediction approaches into two paradigms: *state-evolution prediction* and *outcome-oriented prediction*. The former focuses on forecasting future system dynamics, health states, or degradation trajectories, whereas the latter directly estimates downstream outcomes such as defects, failures, or product quality.

1) State-Evolution Prediction: It predicts the evolution of systems over time and usually combines state estimation with model-based state propagation. Mapping mainly reconstructs $\hat{\mathbf{x}}_t$ from current observations, and prediction extends this process to future time steps. This capability is important for production equipment because wear, thermal drift, and process instability often develop gradually before they become observable [67]. A representation is given by recursive predictive updating

$$\hat{\mathbf{x}}_{t+1|t} = \hat{f}\left(\hat{\mathbf{x}}_t, \mathbf{u}_t\right), \quad \hat{\mathbf{x}}_{t+1} = \hat{\mathbf{x}}_{t+1|t} + K_t\left(\mathbf{y}_{t+1} - h\left(\hat{\mathbf{x}}_{t+1|t}\right)\right) \tag{13}$$

where K_t is the estimator gain. Equation (13) shows the connection between mapping and prediction. In particular, the predictive model uses the current state estimate to predict future states, and new observations are then used to update these predictions. Yuan et al. [68] apply this idea to the monitoring of a machine tool. Their method uses an extended Kalman filter to calibrate the empirical process model online. Then, the updated model supports future-state prediction. This method improves interpretability compared to data-driven monitoring and shows that predictive capability can be built on a continuously updated twin. As shown in Fig. 6, this paradigm treats degradation as a dynamic process [69] and supports early intervention before quality degradation becomes irreversible.

2) Outcome-Oriented Prediction: The second paradigm adopts a more task-oriented approach. It directly predicts manufacturing outcomes that are important for decision-making without estimating the complete future system state (Fig. 7). These outcomes are often sparse or only partially observed. Therefore, virtual metrology and data-driven quality prediction play an important role in this paradigm.

When outcome variables are only sparsely observed, virtual metrology can estimate missing measurements for later prediction tasks. Kang et al. [22] formulate semiconductor failure prediction as a joint learning problem. Their method uses virtual metrology to estimate missing inspection values and improve die-level failure prediction. The model first reconstructs unobserved measurements and then uses them for failure prediction. This approach reduces the need for exhaustive physical testing. It also shows that DTs can recover missing operational information and improve prediction accuracy. Liu et al. [70] present a more process-oriented approach to die-casting manufacturing. They develop a virtual-real interactive DT that models both process states and defect information. Their framework uses XGBoost for in-process quality prediction and deep learning for postprocess defect identification. This integration strengthens the link between process evolution and final product quality.

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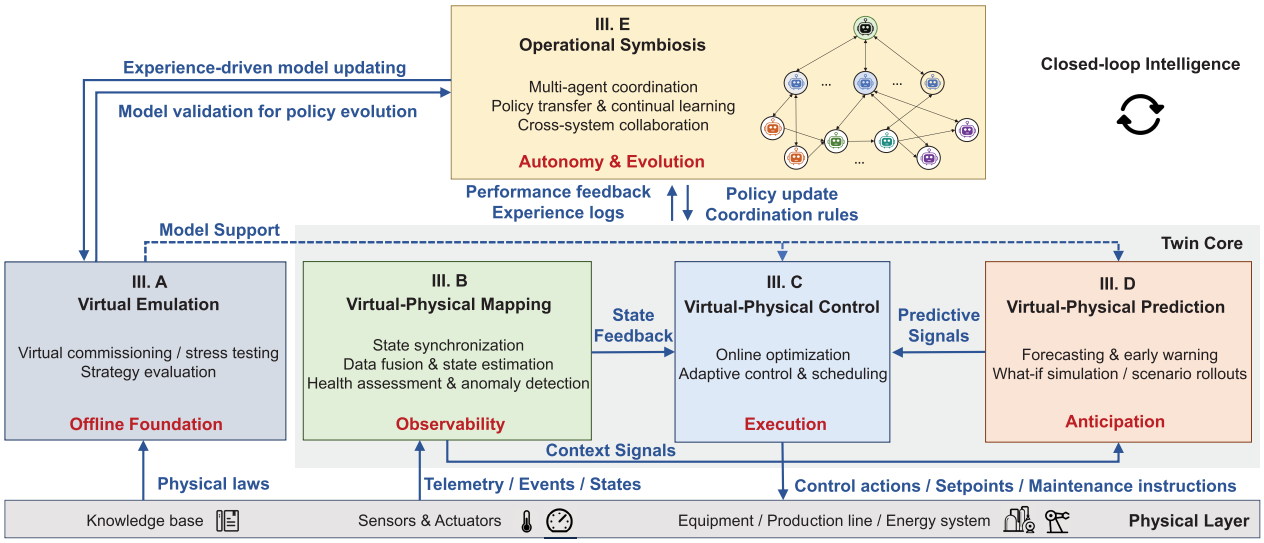

Fig. 8. Operational closed-loop architecture of industrial DTs. The twin core integrates virtual–physical mapping, control, and prediction to form executable closed-loop intelligence over the physical layer. This architecture develops cumulatively but remains configurable. Higher order coordination builds on basic capabilities such as modeling, observability, and execution.

The outcome-oriented paradigm also enables predictive inspection in manufacturing systems. Wang et al. [71] integrate predictive intelligence into an inspection framework for printed circuit board manufacturing. Their framework links descriptive reconstruction with prescriptive management through predictive analysis. Although the system has a broader scope than a conventional DT, it shows how outcome prediction can support early warning and proactive quality assurance. From the perspective of *closed-loop intelligence*, virtual–physical prediction provides anticipatory information for decision-making without directly controlling the physical system. Its defining feature is the inference of future states, outcomes, or risks from current operational information. Prediction can support early warning and decision-making independently, or provide anticipatory inputs for executable control.

E. Toward Operational Symbiosis

Because the preceding capability levels are tightly interconnected, it becomes essential to describe the relationships among them. Fig. 8 summarizes the layered operational architecture of industrial DTs, where virtual emulation, mapping, control, and prediction form a progressively coupled twin core over the physical layer. In particular, virtual–physical mapping provides real-time state estimation $\hat{\mathbf{x}}_t$ from telemetry and event streams, establishing system observability. Based on this, virtual–physical control generates executable actions $\mathbf{u}_t$ that are deployed to the physical layer, forming the primary actuation loop. In parallel, virtual–physical prediction produces predictive signals that anticipate future system evolution, which are fed back into control for proactive decision-making. These interactions create a tightly coupled perception–decision–anticipation structure.

The architecture develops cumulatively. Virtual emulation provides the offline foundation, mapping establishes observability, control enables physical execution, and prediction adds anticipatory capability. Operational symbiosis further extends these functions through coordination among multiple loops. It also relies on shared operational context and continuous adaptation based on accumulated experience. In this stage, multiple cyber–physical components interact closely, exchange feedback, and adapt together over time. Therefore, system behavior is governed not by a single feedback loop, but by the coordinated dynamics of interacting loops, forming a *system-of-systems* structure. Operational symbiosis should be viewed as an emerging and forward-looking capability regime. Current studies more commonly demonstrate partial elements, such as networked coupling, context-aware coordination, or continual model and policy updating. It can be characterized by the following representative forms of coupling.

1) Cross-Loop Coupling: The first form of symbiosis arises when the traditionally separated loops of perception, prediction, and control become tightly coupled. In practical systems, estimation errors, delayed observations, and control actions interact in nontrivial ways, leading to feedback dependencies across layers.

This phenomenon is particularly evident in cyber–physical power systems, where observability and controllability are jointly constrained. Yuqi et al. [72] show that cascading failures emerge from the mismatch between observable and controllable subspaces, and that mitigation strategies must be applied simultaneously across both the cyber and physical layers. This view shows that closed-loop intelligence cannot be treated as a set of independent modules. Operational symbiosis emerges when the DT evolves beyond an estimation–prediction–control pipeline. Instead, these functions interact within a tightly coupled dynamical system and evolve together over time.

2) Multientity Symbiosis: A deeper form of symbiosis appears when multiple physical entities and their DTs become structurally interdependent. This type of interdependence is common in intelligent manufacturing. Ye et al. [73] show that

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machine degradation and feedstock quality can influence each other in manufacturing networks. Low-quality inputs accelerate machine wear, while degraded machines further reduce product quality. As a result, local disturbances can propagate through coupled physical and operational relationships. This form of symbiosis can be represented as a networked system

$$\hat{\mathbf{x}}_{t+1}^{(i)} = f^{(i)}\left(\hat{\mathbf{x}}_t^{(i)}, \left\{\hat{\mathbf{x}}_t^{(j)}\right\}_{j\in\mathcal{N}(i)}\right) \tag{14}$$

where $\mathcal{N}(i)$ denotes the set of entities interacting with entity i, and each entity evolves according to its own dynamics and the states of neighboring subsystems. In symbiotic IoT systems, temporal dynamics and network structures jointly affect system behavior. Huang et al. [74] use graph neural networks to model these interactions and show that reliable operation requires the model to capture both temporal evolution and structural dependencies.

3) Context-Aware Adaptive Coordination: Symbiosis involves context-aware coordination and adaptive decision-making across subsystems [75]. In this case, the system responds to current states and interprets the surrounding context, adjusting its behavior as operating conditions change. Shen et al. [76] propose a context-aware reactive planning framework for handling unexpected situations. Their framework first identifies unexpected events through event evolution analysis and then refines the context and updates decisions. The architecture connects multiple subsystems through a symbiotic computing paradigm. Conventional policies often make decisions based on system states, but context-aware policies also consider situational information and can respond to unforeseen conditions.

4) Symbiosis as the Emergence of System-Level Intelligence: From the perspective of *closed-loop intelligence*, operational symbiosis evolves DTs from loop-level intelligence to system-level intelligence. Mapping, control, and prediction provide essential functions, but they usually operate within individual loops or subsystems. On the contrary, symbiosis is defined by interaction, interdependence, and coevolution across components. Three key properties distinguish this stage.

1) *Interdependence*: states and decisions are closely coupled across system components.
2) *Context-awareness*: decisions incorporate global situational information instead of only relying on local system states.
3) *Coevolution*: models, policies, and system behaviors continuously evolve through ongoing interaction within real-world environments.

Therefore, operational symbiosis can be viewed as a coupled dynamical system over a set of interacting twins

$$\hat{\mathbf{x}}_{t+1}^{(i)} = f^{(i)}\left(\hat{\mathbf{x}}_t^{(i)}, \mathbf{u}_t^{(i)}, \mathbf{c}_t, \left\{\hat{\mathbf{x}}_t^{(j)}\right\}_{j\in\mathcal{N}(i)}\right) \tag{15}$$

$$\mathbf{u}_t^{(i)} = \pi^{(i)}\left(\hat{\mathbf{x}}_t^{(i)}, \mathbf{c}_t\right) \tag{16}$$

where $\mathbf{c}_t$ represents the shared operational context. Unlike isolated loops, both state evolution and decision policies depend on cross-system interactions and global context, forming a networked closed-loop structure.

At a higher level, symbiosis further introduces a slow-timescale evolution of models and policies driven by accumulated experience

$$\left(\pi^{(i)}, f^{(i)}\right) \leftarrow \mathcal{M}\left(\left(\pi^{(i)}, f^{(i)}\right), \mathcal{D}_t\right) \tag{17}$$

where $\mathcal{D}_t$ denotes experience logs collected from system operation and $\mathcal{M}(\cdot)$ represents the update mechanism. This captures the essence of experience-driven adaptation illustrated in Fig. 8, where policy evolution and model updating form a second-order feedback loop.

IV. Cross-Lifecycle Implications of Operational Intelligence

Although this review focuses on operational DTs, operational intelligence is not an isolated lifecycle capability. In industrial systems, operation is where closed-loop intelligence is most directly instantiated: upstream design choices shape its effectiveness, while operational feedback informs design refinement, predictive maintenance, and lifecycle knowledge evolution. Therefore, operation serves as the central link among the lifecycle stages through continuous feedback.

Operational DTs also change the way design is evaluated and updated. In conventional workflows, design assumptions are defined before deployment and are rarely revised during operation [77]. DTs make this process more dynamic. Real-time system states can reveal whether the original design assumptions remain valid. Therefore, operation provides continuous feedback for design improvement, and frequent compensatory actions may indicate that the original design lacks robustness. Differences between predicted and observed behavior also expose simplified or inaccurate assumptions. For example, repeated DT-based compensation for spindle thermal drift reveals weaknesses in the original thermal design of the machine tool. This operational evidence can guide improvements in the cooling configuration or structural parameters. The relationship is asymmetric but important: *design provides the initial structure, and operation provides evidence for its refinement.*

Maintenance intelligence also builds on operational observability and prediction. Virtual–physical mapping provides reliable information on the current system state. Prediction further estimates how degradation may develop over time. These capabilities allow maintenance to move from periodic inspection toward condition-aware and risk-informed intervention [69], [78], [79]. Over longer time horizons, operational logs, model updates, validated policies, and maintenance outcomes gradually form reusable lifecycle knowledge. This knowledge can support future design improvement, maintenance-policy updates, and continuous asset management.

V. Open Challenges and Promising Directions

Building on the preceding analysis, we identify several open challenges and promising directions for advancing operational DTs, as shown in Fig. 9.

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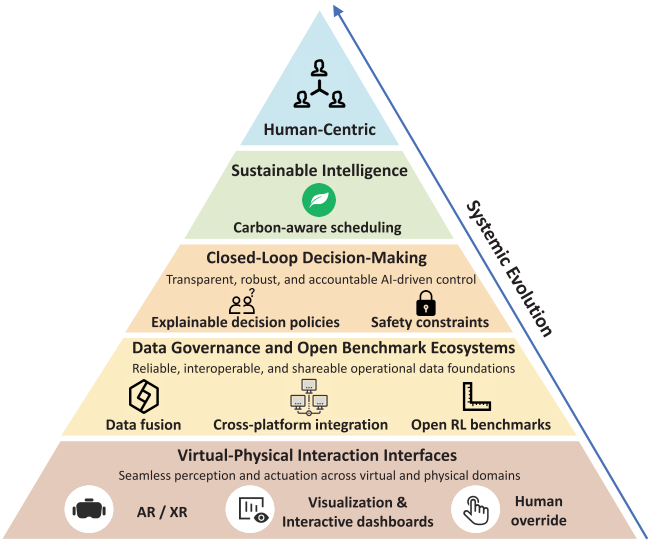

Fig. 9. Systemic evolution toward human-centric closed-loop intelligence. Operational DTs evolve from virtual–physical integration and robust decision-making toward energy-aware optimization and human-centered collaboration.

A. Virtual–Physical Interaction Interfaces

Operational DTs require seamless interfaces between virtual and physical systems. These interfaces support real-time perception, interaction, and actuation. They can also integrate AR [80], XR [81], dashboards, and other visualization tools to support human interaction with the twin.

The main challenge is achieving seamless synchronization between virtual models and physical systems. This requires effective data fusion, latency management [82], and integration of heterogeneous data sources. Virtual–physical interfaces must also support real-time decision-making instead of serving only as visualization tools. They should present system changes in a clear and meaningful way [83], [84], [85]. Adaptive and context-aware functions are also needed to improve situational awareness under changing operating conditions. The ultimate goal is to build an interactive and adaptive system that closely connects human operators with both virtual and physical processes. Such a system should allow operators to understand system conditions and participate in decision-making in an intuitive way. Continuous operational feedback can further support the evolution of human-centric closed-loop intelligence. This interaction can improve operational efficiency while maintaining system safety. However, several challenges need to be addressed to achieve this goal.

1) Maintaining real-time synchronization between virtual models and their physical counterparts.
2) Combining heterogeneous data from sensors, IoT devices, and other sources into a unified real-time feedback loop.
3) Minimizing communication latency between virtual and physical systems to support timely and effective decisions.
4) Designing intuitive and user-friendly interfaces that improve human interaction with DT systems.

B. Data Governance and Open Benchmark Ecosystems

Section III describes the core functional capabilities of operational DTs. However, these capabilities cannot function effectively without appropriate data infrastructures and evaluation mechanisms. Industrial systems usually integrate data from many different sources. Their architectures are fragmented, and data semantics vary across platforms. These inconsistencies reduce the reliability of closed-loop intelligence and make knowledge transfer between systems more difficult [86].

1) Data Governance for Operational Intelligence: Operational DTs depend on continuous interactions among streaming observations $\mathbf{y}_t$, estimated states $\hat{\mathbf{x}}_t$, and control actions $\mathbf{u}_t$. These interactions require different system components to exchange data in a consistent and reliable way. The data must also remain accessible throughout the operational process. However, in practical manufacturing systems, meeting these requirements is difficult. Industrial data originate from multiple sources. They may be collected at different sampling rates and may also contain missing observations [87]. Data governance therefore provides an essential basis for closed-loop intelligence. It transforms raw industrial data into information that can be consistently interpreted and used by the DT system. This process mainly covers three aspects.

1) *Consistency:* Data collected from sensors, control systems, and enterprise platforms must be aligned in terms of both time and semantics. Time synchronization allows observations from different sources to represent the same system state. Semantic alignment provides a common basis for interpreting variables across different systems [88].
2) *Reliability:* Industrial data may include noise, missing values, and corrupted records. Closed-loop operation needs mechanisms for data validation and anomaly filtering [89]. These mechanisms are important for prediction and decision-making tasks because errors in $\mathbf{y}_t$ can spread through subsequent processing stages and accumulate over time. Data lineage and version control provide additional support by recording how data are generated, modified, and used. Such records help preserve traceability and reproducibility when the operational environment changes [90].
3) *Accessibility:* Operational intelligence spans several system layers, from edge devices to cloud platforms and enterprise systems. Data governance should enable secure and efficient data exchange across these layers [91]. It should also ensure that different systems can access and interpret the required data. At the same time, such data sharing must satisfy privacy and security requirements.

2) Open Benchmark Ecosystems for System Evolution: In addition to data availability, the industrial DT community still lacks common benchmarks for evaluating intelligent capabilities. Many studies use proprietary datasets and task-specific metrics. In this case, researchers often cannot compare different methods under the same conditions. These differences also make it difficult to determine whether a method can generalize

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to other industrial settings. Open benchmark ecosystems are therefore needed to establish a shared basis for evaluation:

1) *Standardized task definitions:*. Core operational problems (e.g., scheduling, anomaly detection, predictive maintenance, and adaptive control) should be formulated as well-defined benchmark tasks [92], [93]. A common task definition gives researchers a consistent setting for method comparison. It also helps to clarify how different algorithmic approaches solve particular industrial problems;
2) *Shared datasets:* Benchmark datasets should capture the multimodal and temporal features of industrial systems. Representative datasets should cover sensor streams, control signals, event logs, and other relevant information [94]. More importantly, datasets must retain the connection between system perception and subsequent decisions. This connection enables researchers to evaluate an entire closed-loop process;
3) *Unified evaluation protocols:* Evaluation should not focus only on prediction accuracy. It should also examine latency, robustness, energy efficiency, and safety compliance [95]. In addition, the evaluated methods must produce reliable decisions that satisfy physical safety requirements.

The absence of standardized benchmarks makes results harder to reproduce and slows the accumulation of knowledge between studies. Open and consistent evaluation frameworks can provide researchers with a shared basis for comparing methods and applying solutions to different industrial domains. Therefore, data governance and benchmark ecosystems serve as two important foundations for operational DTs. Data governance keeps industrial data reliable, consistent, and interoperable between systems. In turn, benchmark ecosystems allow researchers to assess closed-loop methods under common conditions and observe how their performance improves over time.

C. Trustworthy Closed-Loop Decision-Making

As operational DTs move from passive monitoring toward active decision-making, trustworthiness becomes a key issue. Virtual–physical control allows the system to perform automated actuation and optimization. However, strong performance alone does not guarantee reliable decisions. These decisions should also be transparent, safe, and consistent with human needs. In industrial settings, closed-loop decisions directly influence physical processes and even human safety [96]. Therefore, operational DTs need stricter safeguards than purely digital intelligence systems. A control policy is inadequate if users cannot understand, verify, or override its decisions when necessary.

1) *Decision transparency* is important for establishing trust in operational DTs. Many advanced methods rely on opaque models, making their decisions difficult to interpret. In this case, operators may struggle to understand why a particular action is selected. This limitation hinders the deployment of these methods in real industrial environments [97]. Hybrid approaches offer one possible solution. They combine data-driven models with interpretable structures or physics-informed constraints, making system behavior easier for operators to examine and validate.
2) *Safety and robustness* should be integrated into the decision loop. Industrial systems must operate within strict physical and operational constraints [98]. An unsafe action can damage equipment or interrupt production. Therefore, control and optimization methods need explicit safety constraints, fallback strategies, and uncertainty-aware decision mechanisms [99]. In addition, DTs can further improve this process by testing candidate actions in a virtual environment before the physical system executes them.
3) *Human-centric interaction* is an important part of closed-loop intelligence [100]. Operational DTs should support both *human-in-the-loop* and *human-on-the-loop* paradigms. In these settings, humans remain involved in supervision, validation, and high-level decisions [101]. The role of humans also varies with different DT capabilities. In virtual emulation, humans mainly participate in model design and validation. In mapping and control, they focus more on state interpretation and supervisory control. For predictive functions, humans evaluate potential risks. Symbiotic settings require closer coordination between humans and the DT system. Interactive interfaces and explainable outputs can help operators understand system recommendations. Adjustable control authority also allows them to intervene when necessary. Human experts can provide contextual knowledge that is difficult to incorporate directly into models, and DTs can then use this feedback to refine their policies.

D. Sustainable Operational Intelligence

Operational DTs are expected to contribute to sustainable industrial operation. As manufacturing becomes increasingly data-driven, environmental impact becomes a more important concern. DTs can support sustainability-oriented decisions by linking real-time monitoring with prediction and control. Virtual–physical mapping allows the system to continuously track energy consumption and resource conditions [102]. Prediction models can use these observations to estimate future demand and detect possible inefficiencies. The resulting information can then support control strategies that adjust operating conditions and reduce unnecessary energy use and emissions. Operational DTs also need to consider performance and sustainability within the same closed-loop process. For example, a control policy may optimize production throughput while also reducing energy consumption [103]. In practice, these goals may conflict; e.g., reducing energy use and carbon emissions may compromise production efficiency or operational reliability. The digital infrastructure underlying DTs also incurs resource costs. Sensing, communication, simulation, and learning all require computation and energy. Sustainable operational intelligence should account for both the improvements achieved in physical processes and the resources consumed by the digital system itself.

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VI. Conclusion

This work investigates industrial DTs through the lens of operational closed-loop intelligence. By integrating lifecycle evolution with virtual–physical relationships, DT capabilities are organized into five levels: virtual emulation, virtual–physical mapping, control, prediction, and operational symbiosis. This framework characterizes how DTs evolve from offline analytical representations toward observable, executable, anticipatory, and increasingly coordinated operational systems. The lifecycle-oriented capability matrix further highlights operation as the central stage where sensing, decision-making, and actuation converge, while operational feedback continuously supports design refinement, predictive maintenance, and lifecycle knowledge evolution. Further progress toward operational symbiosis depends on reliable virtual–physical interaction, interoperable data governance, trustworthy decision-making, sustainable optimization, and effective human collaboration. Addressing these challenges will enable DTs to develop into adaptive and dependable infrastructures for next-generation industrial intelligence.

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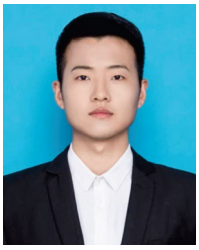

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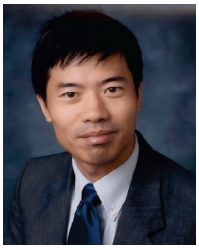

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