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Digital Twin-Assisted Intelligent Control Framework for Real-Time Optimization of Cyber-Physical Systems in Smart Manufacturing

Nimmi A. Ekka

Lecturer Department of Computer Science Engineering Government Women Polytechnic, Ranchi, Jharkhand

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ABSTRACT

Cyber-physical production systems require continuous coordination between physical equipment, computational models, production objectives, and operational constraints. Although digital twins support monitoring, simulation, and prediction, many manufacturing implementations remain limited to visualization or offline decision support. This paper proposes a Digital Twin-Assisted Intelligent Control Framework for real-time optimization of cyber-physical systems in smart manufacturing. The framework combines industrial data acquisition, semantic interoperability, edge computing, hybrid physics-data digital-twin models, state estimation, predictive analytics, hierarchical optimization, safety-constrained control, and human oversight. A credibility mechanism continuously evaluates synchronization error, model uncertainty, data quality, and operating-domain validity before permitting control actions. At the decision level, model predictive control addresses short-horizon process regulation, deep reinforcement learning supports adaptive policy selection, and constraint programming handles production scheduling and resource allocation. A safety shield verifies proposed actions against equipment, process, quality, and cybersecurity constraints before commands are transmitted to programmable logic controllers or manufacturing execution systems. The study follows a design-science methodology and specifies a reproducible validation protocol for a flexible machining and assembly cell. Evaluation scenarios include tool wear, quality drift, machine failure, demand variation, communication delay, energy constraints, and malicious data manipulation. Proposed performance indicators cover throughput, overall equipment effectiveness, energy consumption, defect rate, recovery time, decision latency, twin fidelity, and unsafe-action rejection. The framework provides a standards-aligned foundation for developing adaptive, secure, explainable, and real-time digital-twin control systems in smart manufacturing.

1. Introduction

Smart manufacturing systems integrate sensors, industrial networks, programmable logic controllers, robots, machine tools, manufacturing execution systems, analytics platforms, and human operators. These elements collectively form cyber-physical production systems in which computational decisions affect physical processes and physical observations continuously update computational models. The resulting interdependence creates opportunities for adaptive production but also introduces uncertainty, nonlinear behavior, equipment degradation, communication delays, heterogeneous data, and conflicting operational objectives.

A digital twin provides a continuously updated digital representation of an observable manufacturing element or process. The ISO 23247 series describes a manufacturing digital-twin framework covering observable manufacturing elements, digital-twin entities, users, services, and information exchange. Its recent extensions also address digital threads and the composition of multiple digital twins across manufacturing lifecycles.

Existing studies show that digital twins can support bidirectional manufacturing control, quality prediction, asset tracking, process optimization, line reconfiguration, energy management, and human-machine knowledge integration. For example, a 2026 hybrid digital-twin study combined discrete-event simulation, constraint programming, industrial Internet of Things data, and edge execution, reporting reductions in simulated production time and energy consumption. A 2025 manufacturing-line study used a process digital twin, ontology, optimizer, and automatically generated simulation to identify reconfiguration plans after disturbances.

Nevertheless, several limitations remain. First, many digital twins provide monitoring without verified virtual-to-physical actuation. Second, high-fidelity simulations may be too computationally intensive for real-time control. Third, purely data-driven controllers can generate unsafe recommendations outside their training distribution. Fourth, process control, scheduling, quality, energy, and maintenance decisions are frequently optimized separately.

Corresponding Author: nimmiekka@gmail.com

Finally, digital-twin fidelity, cybersecurity, operator authority, and fallback behavior are not always integrated into the control architecture.

This paper addresses these limitations by proposing a credibility-aware, safety-constrained, hierarchical control framework for smart manufacturing. The principal contributions are:

1. A layered digital-twin architecture connecting physical production resources, edge intelligence, hybrid models, predictive services, optimization, and governed actuation.
2. A credibility mechanism that evaluates model residuals, uncertainty, synchronization, data quality, and operating-domain validity.
3. A hierarchical optimization structure combining model predictive control, reinforcement learning, and constraint programming.
4. A safety shield that prevents infeasible or high-risk virtual decisions from reaching production equipment.
5. A reproducible validation protocol covering operational performance, real-time behavior, resilience, cybersecurity, and human oversight.

The following research questions guide the study:

RQ1: How can a digital twin support real-time closed-loop optimization without displacing deterministic machine-level control?

RQ2: How can physics-based and data-driven models be combined while maintaining measurable model credibility?

RQ3: How can process, quality, energy, maintenance, and scheduling objectives be coordinated within one control framework?

RQ4: How can safety, cybersecurity, explainability, and human authority be embedded in digital-twin-assisted control?

2. Literature Foundation

2.1 Recent open-access research

Table 1 summarizes recent journal studies directly relevant to digital-twin-assisted intelligent control. The studies are ordered from the most recent publication. The relevance score measures direct alignment with the present framework-design topic rather than overall publication quality.

Table 1

Recent journal studies relevant to the proposed framework

Study	Keywords and application	Abstract-based contribution and key finding	Reported limitation or future work	Relevance
Amirkhanova et al. (2026)	Closed-loop twin; constraint programming; edge computing; energy scheduling	Proposed a three-layer hybrid architecture combining simulation, production scheduling, and edge control. A bakery-model evaluation reported **24.4% lower production time, 23% energy savings, and elimination of simulated quality-window violations**.	Operational results were primarily simulation-based; full physical deployment and wider industrial replication remain necessary.	**9.7**
Heide et al. (2025)	Bidirectional digital twin; CNC milling; process monitoring; adaptive manufacturing	Implemented bidirectional communication between a five-axis machining center and a dexel-based process simulation using machine-native signals.	Requires broader industrial validation, additional adaptive control functions, and evaluation under more varied disturbances.	**9.6**
Fu et al. (2025)	Line reconfiguration; ontology; optimization; disturbance handling	Combined disturbance monitoring, capability-based resource modeling, configuration optimization, and accelerated simulation. The battery-line case prevented modeled throughput reductions of **26% and 63%**, with an average optimizer time of **0.03 seconds**.	Further work should address additional disturbance types, distributed factories, uncertainty in resource capability, and implementation across different manufacturing sectors.	**10.0**

Ullah, Younas, and Saharudin (2025b)	Cognitive twin; quality management; predictive analytics; feedback control	Proposed a cognitive-twin framework that continuously monitors manufacturing data and applies predictive analytics to real-time quality optimization.	More detailed physical case validation, clearer real-time inspection mechanisms, and stronger reporting of experimental support were identified as important.	**9.3**
Ullah, Younas, and Saharudin (2025a)	Asset tracking; Wi-Fi fingerprinting; deep learning; flexible manufacturing	Integrated indoor localization, deep-learning prediction, and digital-twin concepts to support asset monitoring and flexible manufacturing operations.	Seamless integration of localization models with the operational digital twin remains essential for complete closed-loop implementation.	**8.5**
García et al. (2024)	Human-machine knowledge; legacy equipment; retrofitting; SMEs	Developed a three-layer learning ecosystem using data streams, data models, and knowledge models. Case studies used real milling-machine and foundry data; the induction-furnace application reported approximately **9% improvement in power efficiency**.	Future studies should examine workforce learning, long-term adoption, transfer between factories, and integration with proprietary industrial systems.	**8.8**
Ullah and Younas (2024)	Flexible manufacturing; dynamic optimization; closed-loop control	Combined simulation, data acquisition, and machine learning to reproduce flexible-manufacturing behavior and support dynamic optimization and control.	Wider industrial deployment, interdisciplinary implementation, interoperability, and longitudinal validation are required.	**9.2**

Khdoudi et al. (2024)	Deep reinforcement learning; full-duplex twin; injection molding	Proposed a specific-purpose, full-duplex digital twin that combines supervised learning and deep reinforcement learning for autonomous process control.	Industrial use requires stronger safety assurance, generalization beyond the molding case, and validation under unseen operating conditions.	**9.7**
Rolofs et al. (2024)	Energy management; CPPS; model-based systems engineering	Defined a conceptual framework integrating physical models, data infrastructure, energy optimization, and manufacturing interfaces.	Real-world implementation and more sophisticated optimization methods were identified as future research needs.	**8.9**
Christ et al. (2023)	Assembly; real production system; virtual commissioning	Demonstrated the implementation of a digital twin and physical production system for assembly-technology research and training.	Model-physical discrepancies, simulation detail, scalability, and expanded industrial evaluation require further study.	**8.1**
Jwo et al. (2022)	Data twin; cyber-physical factory; service architecture	Proposed a data-twin service and cyber-physical factory architecture for constructing, managing, and applying manufacturing data representations.	More comprehensive closed-loop control, standardized semantics, and multi-factory deployment are required.	**8.7**
Liu et al. (2021)	MBSE; shop-floor twin; SysML; MagicGrid	Developed a model-based systems-engineering method for constructing a shop-floor digital twin and linking system requirements, functions, behavior, and architecture.	Runtime intelligence, automated model updating, control verification, and large-scale interoperability remain open development areas.	**8.5**

2.2 Research gap

The literature establishes several necessary components of intelligent digital-twin control, but these components are rarely combined into one governed architecture. Khdoudi et al. demonstrated reinforcement-learning-based autonomous process optimization, while Fu et al. demonstrated rapid line reconfiguration. Heide et al. emphasized bidirectional machine coupling, and Amirkhanova et al. combined edge control with deterministic scheduling. These studies collectively support the feasibility of closed-loop digital twins but also reveal fragmentation between process regulation, scheduling, energy optimization, model management, and safety assurance.

A second gap concerns model validity. A manufacturing twin can become unreliable because of tool wear, sensor drift, unmodeled disturbances, product changes, network delays, or differences between simulated and actual equipment. The proposed framework therefore treats twin credibility as a control variable rather than assuming that the virtual model remains accurate.

A third gap is the relationship between intelligent control and deterministic automation. Time-critical servo, interlock, and emergency-stop functions should not depend on cloud services or nondeterministic learning systems. The proposed framework consequently retains hard real-time control in certified machine controllers and uses the digital twin for supervisory optimization.

3. Research Methodology

The study applies a design-science methodology consisting of five stages:

1. **Problem identification:** Determine the operational and technical barriers preventing digital twins from supporting safe real-time manufacturing control.
2. **Requirement synthesis:** Derive functional and nonfunctional requirements from recent manufacturing studies, digital-twin standards, industrial communication practices, and cybersecurity requirements.
3. **Artifact design:** Develop the proposed architecture, mathematical formulation, control workflow, data model, and safety-governance mechanism.

Corresponding Author: nimmiekka@gmail.com

4. **Analytical evaluation:** Map architectural components to the identified requirements and examine expected behavior under representative disturbances.

5. **Experimental validation design:** Specify a hardware-in-the-loop and physical-cell protocol that can test effectiveness without fabricating results.

The unit of analysis is a flexible manufacturing cell containing machining, material handling, robotic manipulation, inspection, and production-management functions. The artifact is not a replacement for the machine controller. It is a supervisory cyber-physical control framework that observes the manufacturing cell, predicts its future state, identifies an optimized action, validates that action, and coordinates implementation through existing control systems.

4. Proposed Digital Twin-Assisted Intelligent Control Framework

4.1 Architectural principles

The framework is based on six principles:

- **Bidirectional synchronization:** The virtual and physical systems exchange observations, model updates, decisions, and execution feedback.
- **Hierarchical timing:** Control functions are assigned to machine, edge, plant, or cloud layers according to their deadlines.
- **Hybrid intelligence:** Physical mechanisms, historical data, real-time observations, expert rules, and learned models are combined.
- **Credibility-aware autonomy:** Control authority depends on model confidence, data quality, and operating-domain validity.
- **Safety before optimality:** No proposed action is executed unless it satisfies process, equipment, quality, and security constraints.
- **Graceful degradation:** The production system returns to a verified fallback controller when communication, models, or optimization services become unreliable.

Corresponding Author: nimmiekka@gmail.com

Table 2

Layers of the proposed framework

Layer	Principal components	Main functions	Typical timing
1. Physical production	CNC machines, robots, conveyors, tools, sensors, PLCs, inspection devices	Execute manufacturing operations; enforce interlocks and emergency control	Microseconds to milliseconds
2. Edge connectivity	Industrial gateways, OPC UA servers, message broker, time synchronization, local historian	Acquire, validate, timestamp, normalize, and route observations	Milliseconds
3. Digital-twin modeling	Geometry, physics models, state-space models, discrete-event simulation, surrogate models	Represent present state, simulate alternatives, estimate unobserved variables	Milliseconds to seconds
4. Predictive	Anomaly detection, remaining-life	Predict future conditions	Tens of milliseconds to

Layer	Principal components	Main functions	Typical timing
intelligence	prediction, quality prediction, demand estimation	and quantify uncertainty	minutes
5. Optimization and planning	MPC, reinforcement learning, constraint programming, multi-objective optimizer	Select process parameters, schedules, routes, maintenance actions, and energy strategies	Milliseconds to hours
6. Safety and actuation	Constraint checker, safety shield, approval workflow, fallback controller	Verify and transmit authorized actions; monitor execution	Milliseconds to seconds
Cross-cutting governance	Identity management, cybersecurity monitoring, audit logs, model registry, operator interface	Protect, explain, trace, and govern the complete lifecycle	Continuous

Corresponding Author: nimmiekka@gmail.com

4.2 Interoperability and synchronization

The physical-to-digital path begins with sensor, controller, quality, energy, maintenance, and production-order data. Every observation is assigned an equipment identifier, engineering unit, timestamp, quality indicator, and source. OPC UA is suitable for this layer because it supports secure, platform-independent and vendor-independent industrial information exchange, including real-time data, alarms, events, and historical information.

The synchronization service performs:

- clock alignment;
- missing-value detection;
- outlier screening;
- engineering-unit conversion;
- semantic mapping;
- sampling-rate reconciliation;
- duplicate removal;
- communication-delay estimation; and
- data-quality scoring.

Let the received observation at time (t) be:

$$y\_t\hat{}r=y\_t-\delta\_t+v\_t,$$

where (y) is the physical observation, (delta_t) is the communication delay, and (v_t) represents sensor and transmission noise. The synchronization service estimates (delta_t) and prevents stale information from being treated as the current plant state.

4.3 Hybrid digital-twin model

The manufacturing CPS is represented as:

$$x\_t+1=f(x\_t,u\_t,d\_t,\theta\_t)+w\_t,$$

$$y\_t=h(x\_t)+v\_t,$$

where:

- (x_t) is the process and equipment state;
- (u_t) is the control input;
- (d_t) is an observed or unobserved disturbance;

- (theta_t) contains time-varying model parameters;
- (y_t) is the measured output;
- (w_t) and (v_t) are process and measurement noise.

A purely physics-based model may be interpretable but computationally expensive or incomplete. A purely data-driven model can be fast but may fail outside its training domain. The framework therefore combines both:

$$f\_hat\_DT = \alpha\_t\, f\_physics + (1-\alpha\_t) f\_data + f\_residual,$$

where (alpha_t) is dynamically adjusted according to data availability, model error, uncertainty, and the current operating regime. The residual model learns systematic differences between physical-model predictions and actual observations.

State estimation can be performed using an extended Kalman filter, unscented Kalman filter, particle filter, moving-horizon estimator, or a domain-specific observer. The estimator produces both the state estimate (x_t) and uncertainty (P_t).

4.4 Digital-twin credibility

The credibility score determines whether the digital twin may recommend, automatically execute, or merely display a control action:

$$C\_t = \omega\_1\, C\_fidelity + \omega\_2\, C\_data + \omega\_3\, C\_sync + \omega\_4\, C\_domain + \omega\_5\, C\_security,$$

subject to:

$$\Sigma\_i=1\text{^}5 \omega\_i = 1,\ 0 \leq C\_t \leq 1.$$

The components represent:

- **Fidelity:** agreement between predictions and observed behavior;
- **Data quality:** completeness, validity, accuracy, and consistency;
- **Synchronization:** freshness and timing alignment;
- **Domain validity:** whether the current state lies within a validated operating region;
- **Security:** integrity and trustworthiness of the data and model pipeline.

Three operating modes are proposed:

Credibility condition	Control mode
(C_t >= C_auto)	Automatic optimization and governed actuation

Credibility condition	Control mode
(C_assist <= C_t < C_auto)	Operator-assisted decision support
(C_t < C_assist)	Monitoring only; fallback control remains active

This mechanism prevents a degraded or compromised twin from retaining unrestricted control authority.

4.5 Predictive services

Predictive services transform state estimates into decision variables. The framework supports:

- product-quality probability;
- tool-wear and remaining-useful-life estimates;
- machine-failure risk;
- cycle-time and queue predictions;
- energy-use forecasts;
- resource availability;
- order completion and tardiness estimates;
- anomaly probability; and
- confidence intervals for each forecast.

Each prediction is stored with the model version, data window, uncertainty, and expiry time. Expired or low-confidence predictions cannot be used for automatic actuation.

4.6 Multi-objective optimization

At time (t), the optimizer selects a sequence of decisions:

$$U_t=u_t,u_t+1,ldots,u_t+H-1,$$

over horizon (H). The objective is:

$$min_U_t \Sigma_k=0^H-1 [w_T J_T(k) +w_Q J_Q(k) +w_E J_E(k) +w_M J_M(k) +w_D J_D(k) +w_R J_R(k)] +V_f(x_t+H),$$

where:

- (J_T) represents cycle time, makespan, or tardiness;
- (J_Q) represents predicted quality loss;
- (J_E) represents energy consumption or peak demand;
- (J_M) represents maintenance and degradation risk;
- (J_D) represents disruption or schedule deviation;
- (J_R) represents operational and cybersecurity risk;
- (V_f) is a terminal penalty.

The optimization is subject to:

$$x_k \in X_{safe},$$

$$u_k \in U_{admissible},$$

$$g_{quality}(x_k,u_k) \leq 0,$$

$$g_{equipment}(x_k,u_k) \leq 0,$$

$$g_{schedule}(x_k,u_k) \leq 0,$$

$$L_{decision} \leq L_{max}.$$

The weights may be fixed by management policy or modified within approved ranges according to product priority, energy availability, equipment condition, or production disruptions.

4.7 Hierarchical control

The framework divides decision-making into four levels.

Table 3

Hierarchical optimization levels

Level	Decision horizon	Proposed method	Example decision
Machine control	Microseconds-milliseconds	Existing PLC, CNC, servo, or robot controller	Position, velocity, interlock, emergency stop

Level	Decision horizon	Proposed method	Example decision
Process supervision	Milliseconds-seconds	Model predictive control	Feed rate, temperature setpoint, robot speed
Adaptive strategy	Seconds-minutes	Safe reinforcement learning or contextual policy selection	Parameter policy, routing strategy, recovery action
Production coordination	Minutes-days	Constraint programming, mixed-integer optimization, discrete-event simulation	Scheduling, resource allocation, maintenance window

Deep reinforcement learning is not permitted to bypass machine-level interlocks. Its output is treated as a candidate supervisory action and must pass through the safety shield. This arrangement preserves the adaptability demonstrated in reinforcement-learning digital-twin research while addressing the risks of unrestricted learned control.

5. Safety, Cybersecurity, and Human Oversight

5.1 Safety shield

The intelligent optimizer proposes an action (u_t^*). The safety shield transforms or rejects it:

$$u\_t(applied) = \Pi\_[U\_safe(x\_t)](u\_t^*)$$

where (Pi) projects the candidate onto the admissible safe-action set. The action is rejected when no safe projection exists or when the required correction exceeds an approved threshold.

The safety shield checks:

- actuator and machine limits;
- collision conditions;
- thermal and force boundaries;
- process-quality windows;
- tool-life restrictions;
- sequence and precedence constraints;
- worker-presence zones;
- communication freshness;
- model credibility;
- operator-approval requirements; and
- cybersecurity alarms.

5.2 Cybersecurity

IEC 62443 addresses industrial automation and control-system security over the system lifecycle. Its foundational requirements include identification and authentication, use control, system integrity, data confidentiality, restricted data flow,

timely response to events, and resource availability. The standards also apply zones-and-conduits concepts to industrial risk assessment and system segmentation.

Table 4

Cybersecurity controls in the proposed framework

Threat	Potential effect	Framework control
False sensor-data injection	Incorrect state estimation and unsafe optimization	Signed messages, plausibility checks, redundant sensing, anomaly detection
Unauthorized command injection	Physical process manipulation	Mutual authentication, role-based authorization, command signing
Model poisoning	Degraded predictions or malicious policies	Versioned model registry, controlled training data, validation gates
Replay attack	Stale data treated as current	Secure timestamps, sequence numbers, freshness checks
Denial of service	Missed decisions and synchronization	Edge fallback, rate limiting, network segmentation,

Threat	Potential effect	Framework control
	loss	degraded-control mode
Compromised edge device	Manipulated observations or commands	Secure boot, hardware trust, patch management, remote attestation
Insider misuse	Unauthorized parameter or objective changes	Separation of duties, audit logs, approval workflow

5.3 Human authority and explainability

Operators remain responsible for decisions outside the validated autonomy envelope. The interface displays:

- current twin credibility;
- predicted consequence of the proposed action;
- uncertainty range;
- violated constraints;
- optimization objective and trade-offs;
- alternative feasible actions;
- reason for rejection or fallback; and
- model and data versions used.

High-impact actions, including shutdown, maintenance deferral, production-rate increases beyond approved limits, and operation under abnormal conditions, require explicit human authorization.

6. Real-Time Control Workflow

Algorithm 1

Credibility-aware digital-twin control cycle

1. Acquire observations from sensors, PLCs, CNCs, robots, inspection devices, and MES.
2. Validate identity, integrity, timestamp, engineering unit, and data quality.
3. Align observations and update the estimated CPS state.
4. Update hybrid-model parameters and calculate prediction residuals.
5. Calculate digital-twin credibility and uncertainty.
6. Detect anomalies and identify the current operating regime.
7. Generate quality, maintenance, energy, and production forecasts.
8. Run hierarchical optimization within the assigned decision deadline.
9. Pass the candidate action through equipment, process, quality, cybersecurity, and human-authorization constraints.
10. When the action is safe and credibility is sufficient, transmit it to the approved controller.
11. Otherwise, request operator approval, modify the action, or activate fallback control.
12. Observe execution, compare predicted and actual outcomes, update the twin, and append an immutable audit record.

The control cycle is event-driven as well as periodic. Events such as a machine fault, sudden quality deviation, order-priority change, tool-wear threshold, or communication anomaly immediately trigger re-estimation and re-optimization.

7. Validation Design

7.1 Proposed manufacturing testbed

The framework can be validated using a flexible machining and assembly cell containing:

- two CNC machines;
- one industrial robot;

- an automated inspection station;
- a conveyor or automated guided vehicle;
- tool-condition sensors;
- energy meters;
- an industrial edge computer;
- PLC and MES connectivity; and
- an operator dashboard.

The cell produces multiple product variants with different routes, process parameters, quality tolerances, and due dates. A hardware-in-the-loop environment should be established before physical actuation testing. The simulated equipment receives the same commands as the real controller interface, permitting verification of timing, constraint enforcement, and recovery behavior.

7.2 Experimental configurations

Four configurations should be compared:

Configuration	Description
B1: Conventional control	Existing PLC/CNC control with rule-based MES scheduling
B2: Monitoring-only twin	Real-time visualization and prediction without automatic optimization
B3: Optimization twin	Digital twin with MPC and scheduling but no credibility-adaptive autonomy
P1: Proposed framework	Hybrid twin, hierarchical optimization, credibility mechanism, safety shield, cybersecurity controls, and fallback behavior

7.3 Disturbance scenarios

Table 5

Validation scenarios

Scenario	Disturbance	Expected framework response
S1	Gradual tool wear	Update wear estimate, adjust process parameters, schedule tool replacement
S2	Unexpected machine failure	Reallocate operations, regenerate schedule, evaluate alternate routes
S3	Quality drift	Detect residual change, identify influential variables, tighten control window
S4	Rush order	Re-optimize schedule while respecting quality and equipment constraints
S5	Energy-demand restriction	Shift flexible operations and

Scenario	Disturbance	Expected framework response
		modify setpoints without violating due dates
S6	Sensor failure	Use redundant measurements or state estimation; reduce credibility
S7	Communication delay	Detect stale data, suspend automatic actions, use edge fallback
S8	False-data injection	Trigger integrity and plausibility alarms; isolate affected data source
S9	Previously unseen operating state	Detect out-of-distribution condition and request operator supervision
S10	Worker enters shared robot zone	Override optimizer and enforce certified safety behavior

Each scenario should be executed at several disturbance intensities and repeated with controlled random seeds. At least 30 independent simulation replications are recommended for stochastic scheduling and failure scenarios. Physical experiments should use the maximum safe number of replications permitted by equipment availability and risk controls.

7.4 Performance indicators

Table 6

Evaluation metrics

Category	Metric	Calculation or interpretation
Productivity	Throughput	Conforming units produced per unit time
Productivity	Overall equipment effectiveness	Availability × performance × quality
Time	Mean cycle time	Average completion time per product
Delivery	Tardiness	Delay beyond order due date
Quality	Defect rate	Nonconforming units ÷ total units
Energy	Specific energy consumption	Energy consumed ÷ conforming unit
Maintenance	Unplanned downtime	Time lost because of unscheduled failures

Category	Metric	Calculation or interpretation
Resilience	Recovery time	Time from disturbance detection to stable production
Twin fidelity	State-estimation error	RMSE or normalized prediction error
Synchronization	Twin lag	Difference between physical event and virtual update
Intelligence	Prediction accuracy	F1, AUROC, MAPE, RMSE, or calibrated probability score
Real time	Decision latency	Time from event detection to verified command
Safety	Unsafe-action rejection rate	Unsafe candidates blocked ÷ unsafe candidates generated
Reliability	Deadline-miss rate	Decisions exceeding permitted deadline ÷ total decisions

Corresponding Author: nimmiekka@gmail.com

Category	Metric	Calculation or interpretation
Security	Detection and containment time	Time to identify and isolate malicious activity
Human factors	Explanation usefulness	Operator rating and task-completion assessment

7.5 Hypotheses

The following hypotheses can be tested:

H1: The proposed framework improves throughput and overall equipment effectiveness compared with conventional and monitoring-only configurations.

H2: The proposed framework reduces defect rate and specific energy consumption without increasing safety violations.

H3: Credibility-adaptive control reduces inappropriate automatic actions under sensor failure, model drift, and unseen operating conditions.

H4: Hierarchical optimization reduces disturbance-recovery time compared with fixed-rule scheduling.

H5: Edge execution reduces decision latency and deadline misses compared with cloud-only execution.

H6: The safety shield blocks all deliberately generated actions that violate encoded equipment and process constraints.

For normally distributed measurements, analysis of variance followed by an appropriate post-hoc procedure may be used. Otherwise, Kruskal-Wallis and pairwise nonparametric tests can be applied. Confidence intervals, effect sizes, and exact sample sizes should be reported in addition to significance values.

8. Analytical Design Evaluation

Because this paper proposes a framework rather than reporting a completed

deployment, its present evaluation examines requirement coverage instead of claiming numerical performance.

Table 7

Requirement-to-design traceability

Requirement	Design mechanism	Verification approach
Real-time response	Edge execution, hierarchical deadlines, fast surrogate models	Measure end-to-end latency and deadline misses
High model fidelity	Hybrid modeling, residual learning, continuous state estimation	Compare predictions with synchronized observations
Adaptation	Online parameter updates, regime detection, safe RL policy selection	Introduce drift and unseen disturbances
Multi-objective optimization	MPC, reinforcement learning, constraint programming	Compare Pareto performance and operational KPIs
Safe actuation	Safety shield, admissible-action projection, machine interlocks	Inject infeasible and hazardous candidate actions
Graceful	Credibility	Disconnect

Requirement	Design mechanism	Verification approach
degradation	thresholds and fallback control	sensors, models, and communication links
Interoperability	OPC UA information exchange and ISO 23247 alignment	Connect heterogeneous devices and inspect semantic consistency
Cybersecurity	Zones, conduits, authentication, integrity checking, audit trails	Conduct controlled replay, spoofing, and denial-of-service tests
Explainability	Objective, confidence, constraint, and consequence display	Conduct operator decision and usability studies
Scalability	Modular services and composable twins	Increase machines, data rates, models, and optimization variables

The proposed architecture responds to a central trade-off in digital-twin design: high-fidelity models provide richer analysis, while real-time control requires bounded computation. The framework addresses this through model hierarchies. A fast

surrogate executes in the control path, while detailed simulations evaluate longer-horizon alternatives or update the surrogate outside the immediate deadline.

The architecture also separates recommendation quality from permission to act. A high-performing learning model does not automatically receive authority. Authority depends on data integrity, synchronization, uncertainty, validated operating range, safety constraints, and the consequence level of the decision.

The framework's hierarchical structure is consistent with recent evidence. Fast reconfiguration has been demonstrated through optimization and accelerated simulation, bidirectional CNC twins have shown machine-simulation data exchange, and hybrid edge architectures have combined scheduling and closed-loop execution. The proposed framework integrates these capabilities while adding explicit credibility and safety-governance layers.

9. Implementation Roadmap

A staged implementation is recommended.

Table 8

Implementation phases

Phase	Scope	Exit criterion
1. Asset and objective definition	Identify machines, processes, KPIs, constraints, and stakeholders	Approved use case and measurable objectives
2. Connectivity	Instrument equipment and establish secure data acquisition	Required signals available with known quality and latency
3. Monitoring twin	Build synchronized state representation and dashboards	Twin reproduces present operating state within tolerance

Phase	Scope	Exit criterion
4. Predictive twin	Add quality, maintenance, and energy models	Models meet pre-established accuracy and calibration limits
5. Advisory optimization	Generate recommendations without automatic actuation	Operators confirm usefulness and constraint compliance
6. Hardware-in-the-loop control	Test commands against virtual and emulated equipment	Safety, latency, and fallback tests pass
7. Restricted autonomy	Permit low-consequence automatic actions	Credibility and safety thresholds consistently satisfied
8. Scaled deployment	Compose machine, cell, and plant twins	Stable performance across products, shifts, and disturbances

The ISO 23247 framework can guide the definition of observable manufacturing elements and digital-twin entities. ISO 23247-4 addresses information exchange, while the 2026 additions address digital threads and integrated, unified, or federated composition of multiple manufacturing twins.

Corresponding Author: nimmiekka@gmail.com

10. Limitations and Future Research

The proposed framework has several limitations. First, effectiveness depends on sufficient sensor coverage and reliable semantic mapping. Second, encoding all safety, process, and quality constraints may be difficult for legacy equipment. Third, hybrid models require careful calibration and can still fail under severe distribution shifts. Fourth, multi-objective weights may reflect conflicting organizational priorities. Fifth, cybersecurity monitoring can detect many abnormal conditions but cannot guarantee complete protection against unknown attacks.

Future research should implement the framework on a physical flexible-manufacturing cell and report quantitative comparisons against conventional control, monitoring-only twins, and optimization twins without credibility governance. Further work should investigate formal verification of learned supervisory controllers, uncertainty-aware reinforcement learning, federated digital-twin composition, automated semantic model generation, transfer learning between similar machines, privacy-preserving cross-factory learning, and operator trust.

Additional research is needed on self-evolving digital twins that can update models without compromising previously verified safety properties. Such systems require controlled model promotion, rollback mechanisms, digital signatures, change-impact analysis, and continuous regression testing. Human-centered studies should also evaluate whether explanations improve decision quality without creating excessive cognitive load.

11. Conclusion

This paper proposed a Digital Twin-Assisted Intelligent Control Framework for real-time optimization of cyber-physical systems in smart manufacturing. The framework integrates secure industrial data acquisition, edge computing, hybrid digital-twin modeling, prediction, model predictive control, reinforcement learning, constraint-based scheduling, safety verification, cybersecurity, and human oversight.

The central design contribution is credibility-aware autonomy. The digital twin does not receive permanent control authority merely because it can produce an optimized recommendation. Authority is continuously adjusted according to model fidelity, data quality, synchronization, operating-domain validity, uncertainty, and security status.

Corresponding Author: nimmiekka@gmail.com

Candidate actions must also pass through a safety shield before implementation.

The framework preserves deterministic PLC, CNC, servo, robot, and safety functions while using digital-twin intelligence for supervisory optimization. This separation enables advanced adaptive decision-making without placing machine-level safety in a nondeterministic analytics platform. The accompanying validation protocol provides a basis for testing operational performance, real-time response, resilience, safety, cybersecurity, and human factors. A physical or hardware-in-the-loop implementation is the next step required to quantify the framework's industrial benefits.

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