International Journal of Scientific Interdisciplinary Research

Volume: 6; **Issue:** 1
Pages: 404–451

DIGITAL TWIN–ENABLED OPTIMIZATION OF ELECTRICAL, INSTRUMENTATION, AND CONTROL ARCHITECTURES IN SMART MANUFACTURING AND UTILITY-SCALE SYSTEMS

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Doi: 10.63125/pqfdjs15
Received: *21 April 2025;* ***Revised:*** *27 May 2025;* ***Accepted:*** *09 June 2025;* ***Published:*** *22 June 2025.*

Abstract

This quantitative, multi-site study examined whether digital twin–enabled optimization was associated with measurable improvements in electrical, instrumentation, and control (EIC) architecture performance across smart manufacturing and utility-scale systems. The study used a longitudinal, multilevel panel design with clustered observations at asset, system, and site levels. The final analytic sample included 18 cases (10 manufacturing plants and 8 utility-scale segments), 96 systems, and 1,842 assets observed over 180 days, yielding 17,280 system-days after data coverage screening. Composite indices representing observability, synchronization quality, integration readiness, and data integrity demonstrated acceptable internal consistency (α = 0.78–0.88). Multilevel regression results indicated that optimization exposure was associated with lower downtime and improved continuity. Downtime decreased by 0.74 hours per system-month (95% CI −1.05 to −0.43, p < 0.001) and availability increased by 1.9 percentage points (95% CI 1.1 to 2.7, p < 0.001). Efficiency outcomes improved, with normalized loss intensity decreasing by 3.6% (95% CI −5.2 to −2.0, p < 0.001) and voltage deviation indices decreasing by 4.1% (95% CI −6.8 to −1.4, p = 0.003). Integrity outcomes improved, as interruption rates decreased (IRR = 0.86, 95% CI 0.79 to 0.94, p = 0.001) and misoperation-related events declined (IRR = 0.81, 95% CI 0.70 to 0.94, p = 0.006). Data quality improved, with completeness increasing by 1.5 percentage points (95% CI 0.9 to 2.1, p < 0.001) and alignment issue rates decreasing by 0.8 percentage points (95% CI −1.2 to −0.4, p < 0.001). Domain moderation indicated stronger downtime reductions in manufacturing and stronger integrity gains in utilities. Mediation evidence suggested that observability and synchronization quality explained a meaningful portion of reliability and integrity improvements. These findings establish digital twin–enabled optimization as a critical lever for architectural resilience, providing a data-driven framework for scaling EIC systems in high-criticality environments.

Keywords

Digital Twin, EIC Optimization, Smart Manufacturing, Utility Systems.

INTRODUCTION

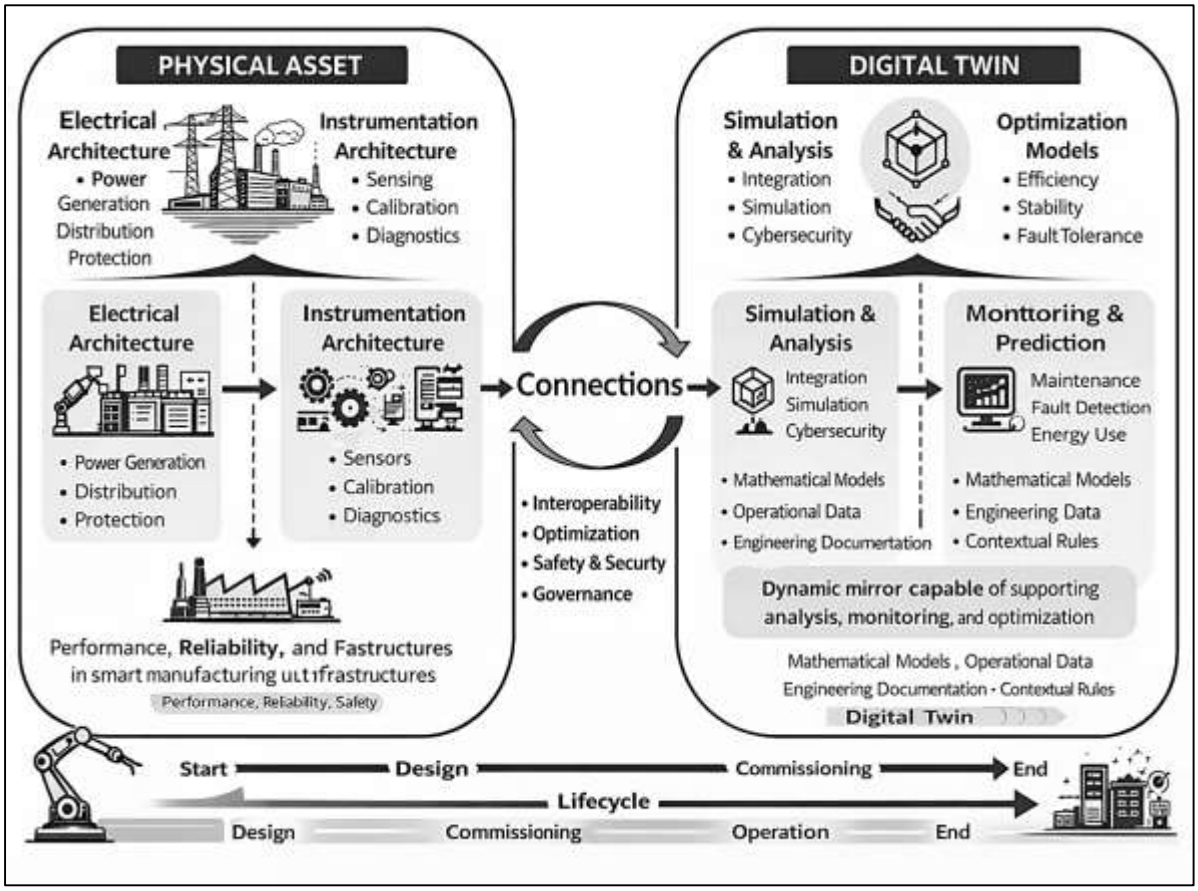
Digital twin technology is defined as a continuously synchronized digital representation of a physical asset, system, or process that reflects its structure, behavior, and operational state through real-time or near-real-time data exchange (Ren et al., 2022). In industrial and infrastructure contexts, a digital twin integrates mathematical models, operational data, engineering documentation, and contextual rules to create a dynamic mirror capable of supporting analysis, monitoring, and optimization. Electrical, instrumentation, and control architectures represent the foundational technical systems through which physical processes are energized, measured, regulated, and safeguarded. Electrical architectures encompass power generation, distribution, protection, grounding, and power quality management across industrial plants and large-scale infrastructures. Instrumentation architectures include sensing devices, signal conditioning, calibration frameworks, data acquisition layers, and diagnostic feedback mechanisms that translate physical variables into reliable digital information. Control architectures consist of automation platforms, logic execution layers, safety systems, supervisory control, and communication hierarchies that transform data into coordinated actions (Pantelidakis et al., 2022). In smart manufacturing and utility-scale systems, these three domains are tightly interwoven, forming cyber–physical infrastructures where performance, reliability, and safety depend on their structural coherence. Optimization within this context refers to the systematic improvement of architectural configurations and operational parameters using measurable performance objectives such as efficiency, availability, stability, fault tolerance, and energy utilization. Digital twin–enabled optimization therefore denotes the use of synchronized digital representations to quantitatively evaluate, compare, and refine EIC architectures across design, commissioning, and operational phases. This framing is internationally significant because electrical grids, manufacturing plants, energy facilities, and process industries form the backbone of economic productivity, public services, and critical infrastructure worldwide (Ladj et al., 2021). Variations in EIC architecture quality directly influence industrial competitiveness, grid reliability, operational safety, and resource efficiency across national and multinational systems.

Smart manufacturing systems are characterized by the integration of cyber–physical components, industrial connectivity, and data-driven coordination across production assets. Within these environments, EIC architectures serve as the primary interface between physical operations and digital intelligence (Liu et al., 2023). Electrical subsystems supply and regulate energy to machines and processes, instrumentation provides situational awareness through high-resolution sensing, and control systems coordinate actions across machines, lines, and facilities. Digital twins introduce a unifying layer that connects these domains into a coherent analytical structure. By maintaining a live correspondence between physical states and digital models, digital twins enable architectural decisions to be evaluated quantitatively rather than heuristically. This capability is particularly relevant in complex manufacturing environments where equipment interactions, process variability, and operational constraints limit the effectiveness of static design assumptions. Utility-scale systems exhibit similar complexity, encompassing transmission networks, substations, renewable generation assets, and protection and automation schemes distributed across wide geographic areas (Redelinghuys et al., 2020). In these systems, EIC architectures govern power flow control, protection coordination, system stability, and fault response under continuously changing conditions. Digital twin representations of such systems enable integrated assessment of electrical behavior, instrumentation accuracy, and control logic interactions under real operating states. The international relevance of this integration arises from the shared reliance of manufacturing and utilities on interoperable, resilient, and auditable EIC infrastructures. Global supply chains and interconnected energy systems require architectures that support consistent performance across regulatory, environmental, and operational contexts. Digital twin–enabled optimization provides a structured means of aligning architectural decisions with measurable system-level outcomes in both industrial production and large-scale utility operation (Kuruvatti et al., 2022).

Interoperability is a central consideration in optimizing EIC architectures through digital twin frameworks. Industrial and utility environments typically comprise heterogeneous components sourced from multiple vendors and deployed across different technological generations (Bevilacqua et al., 2020). Electrical equipment, instrumentation devices, and control platforms often operate using

diverse protocols, data formats, and configuration philosophies. Architectural coherence emerges not from uniformity but from structured integration. Digital twins rely on standardized information models, communication interfaces, and semantic alignment to ensure that data exchanged between physical systems and digital representations retains meaning and consistency. In manufacturing, architectural layers must connect enterprise systems, supervisory control, automation platforms, and field devices in a manner that preserves timing, context, and traceability. In utility-scale systems, similar challenges arise when integrating substations, control centers, and enterprise-level analytics (Khalyasmaa et al., 2023). Optimization of EIC architectures within a digital twin context therefore involves evaluating not only component performance but also the effectiveness of integration mechanisms. Communication latency, data resolution, synchronization accuracy, and naming consistency influence the observability and controllability of the system as a whole. Digital twins transform these architectural attributes into quantifiable variables by exposing their impact on control performance, fault detection, and system stability. This perspective shifts architectural optimization from a compliance-oriented exercise to a performance-driven analysis grounded in operational data. At an international level, interoperability-driven optimization supports cross-border manufacturing networks and interconnected power systems that depend on shared technical frameworks and coordinated operational practices (Bado et al., 2022). The ability to evaluate architectural choices quantitatively within a digital twin environment enhances transparency and comparability across sites, organizations, and jurisdictions.

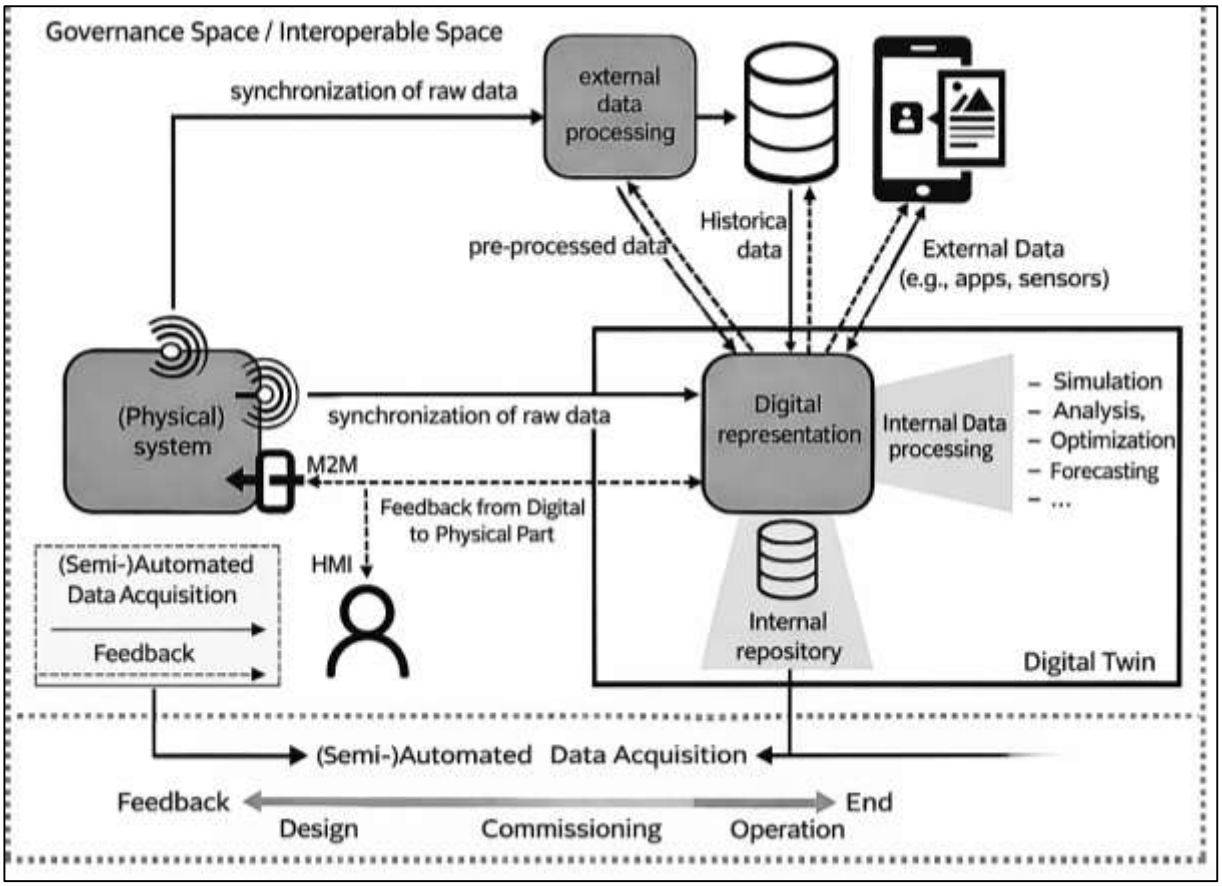
Figure 1: Digital Twin Optimization for Engineering



Model fidelity and integration depth are fundamental to digital twin–enabled optimization of EIC architectures (Jiang et al., 2022). Electrical systems exhibit nonlinear dynamics, transient behaviors, and fault responses that interact with control logic and protective mechanisms. Instrumentation introduces uncertainty through noise, drift, resolution limits, and calibration variability. Control systems impose discrete decision logic, timing constraints, and hierarchical coordination that influence system response. A digital twin that supports architectural optimization must represent these interacting

phenomena with sufficient accuracy to allow meaningful comparison of design alternatives. This requirement extends beyond individual component models to the structure of interactions between subsystems. In manufacturing, discrete-event behaviors such as machine states, material flow, and production scheduling intersect with continuous process dynamics and control loops. In utility-scale systems, fast protection actions coexist with slower supervisory and market-oriented controls (Ruppert & Abonyi, 2020). Digital twins provide a mechanism to integrate these layers into a unified analytical environment. Optimization within this environment involves adjusting architectural parameters such as sensor placement, redundancy strategies, control hierarchy depth, and communication topology, then evaluating their impact on measurable outcomes. Instrumentation architecture directly influences state estimation quality and diagnostic performance, shaping the reliability of control actions and safety responses. Control architecture determines how quickly and accurately the system responds to disturbances and operational changes. Electrical architecture defines energy distribution efficiency and fault containment capability (Bécue et al., 2020). Digital twin–enabled optimization links these domains by allowing architectural configurations to be stress-tested against realistic operating scenarios derived from actual system data. This integrated modeling approach supports quantitative evaluation of architectural coherence rather than isolated subsystem performance.

Figure 2: Engineering Digital Twin Optimization Framework



Optimization techniques applied within digital twin frameworks draw on established methods from control engineering, operations research, and systems engineering (Thelen et al., 2022). Architectural decisions often involve discrete choices such as redundancy levels, network segmentation, and sensor allocation, as well as continuous parameters such as control gains, sampling rates, and protection settings. Digital twins enable these variables to be evaluated within a consistent simulation–measurement loop that reflects real operational constraints. In manufacturing systems, optimization targets may include throughput stability, energy consumption, equipment utilization, and maintenance effectiveness, all of which are influenced by EIC architecture design. In utility-scale

systems, optimization focuses on system security, power quality, reliability indices, and response to disturbances (Sepasgozar et al., 2023). Digital twin environments allow these objectives to be evaluated under varying load conditions, fault scenarios, and operational configurations without disrupting physical operations. Architectural optimization thus becomes a data-supported process where alternatives are compared using quantitative performance indicators rather than static design heuristics. This approach supports international deployment contexts by enabling architectural strategies to be assessed across diverse operating conditions and regulatory environments. The digital twin acts as a neutral analytical layer that accommodates regional differences while preserving consistent evaluation criteria. As a result, EIC architecture optimization becomes a repeatable, evidence-based process applicable across industrial sectors and geographic regions (Lu et al., 2020).

Safety integrity and cybersecurity considerations are inseparable from digital twin–enabled optimization of EIC architectures (Sepasgozar, 2021). Increased connectivity between physical systems and digital models expands the pathways through which faults, misconfigurations, or malicious actions can propagate. Electrical, instrumentation, and control architectures determine how failures are detected, isolated, and mitigated, as well as how access is controlled and monitored. Digital twins provide visibility into these interactions by modeling the behavior of systems under abnormal and adversarial conditions. Architectural choices such as network segmentation, redundancy separation, and control hierarchy influence both operational performance and risk exposure (Newrzella et al., 2021). In manufacturing, inadequate architectural separation between operational and enterprise systems can affect process stability and safety functions. In utility-scale systems, protection and automation architectures play a critical role in preventing cascading failures. Digital twin–enabled optimization allows these architectural aspects to be evaluated quantitatively by simulating fault scenarios, communication delays, and component failures using synchronized operational data. This capability supports a unified view of performance and integrity, where architectural decisions are assessed based on their combined effect on availability, safety margins, and resilience. International infrastructure environments amplify the importance of this integration because systems often operate across organizational boundaries and regulatory regimes (Nwogu et al., 2022). Digital twin–based evaluation provides a common analytical language for assessing architectural robustness in such contexts.

Data governance and lifecycle management determine the long-term effectiveness of digital twin–enabled optimization of EIC architectures (Wang et al., 2023). Digital twins rely on sustained alignment between physical systems, data streams, and digital models across commissioning, operation, and maintenance phases. EIC architectures evolve over time as equipment is upgraded, configurations are modified, and operational strategies change. Instrumentation recalibration, control logic updates, and electrical system reconfiguration introduce variation that must be reflected in the digital twin to preserve analytical validity. Optimization outcomes are only meaningful when data provenance, model assumptions, and configuration context are explicitly managed. In manufacturing environments with legacy systems, achieving this alignment requires disciplined integration strategies and consistent metadata structures (Rasheed et al., 2020). In utility-scale systems, the geographic distribution of assets and organizational separation of responsibilities further increase the importance of standardized data governance. Digital twin–enabled optimization embeds these governance requirements into architectural design by treating data quality, traceability, and synchronization as performance variables. Architectural decisions that support consistent data semantics and configuration management improve the reliability of optimization results. Across international industrial and infrastructure systems, this approach supports comparable performance evaluation and informed architectural decision-making grounded in measurable operational evidence rather than isolated design assumptions (Qi et al., 2021).

The primary objective of this quantitative study is to systematically evaluate and optimize electrical, instrumentation, and control architectures in smart manufacturing and utility-scale systems through the application of digital twin–enabled analytical frameworks. This objective centers on establishing a measurable relationship between architectural design choices and operational performance outcomes by leveraging synchronized digital representations of physical systems. The study seeks to quantify

how variations in electrical distribution structures, instrumentation deployment strategies, control hierarchy configurations, and communication integration patterns influence key performance indicators such as system reliability, operational stability, energy efficiency, fault response behavior, and data integrity. By modeling EIC architectures within a digital twin environment that mirrors real operational conditions, the research aims to transform architectural evaluation from a predominantly qualitative or compliance-driven activity into a data-driven optimization process grounded in observable system behavior. A further objective is to develop a unified analytical structure that captures the interdependencies between electrical subsystems, measurement accuracy, and control responsiveness, recognizing that performance limitations often arise from architectural misalignment rather than component-level deficiencies. The study also aims to quantify the contribution of architectural interoperability and integration depth to system observability and controllability, particularly in environments characterized by heterogeneous assets and multi-layer automation. Through comparative analysis of alternative architectural configurations, the research intends to identify statistically significant performance differentials attributable to sensing density, redundancy allocation, communication latency, and control logic distribution. In addition, the objective includes assessing how digital twin synchronization quality and data consistency affect the reliability of optimization outcomes, thereby establishing architecture-level criteria for trustworthy model-based decision-making. The scope of the objective extends across both smart manufacturing and utility-scale systems to enable cross-domain generalization of findings, reflecting the shared structural and operational characteristics of industrial and critical infrastructure environments. Overall, this objective is directed toward producing empirically grounded evidence that links digital twin–enabled evaluation methods with quantifiable improvements in EIC architectural performance, supporting rigorous optimization of complex cyber–physical systems without reliance on speculative or prescriptive assumptions.

LITERATURE REVIEW

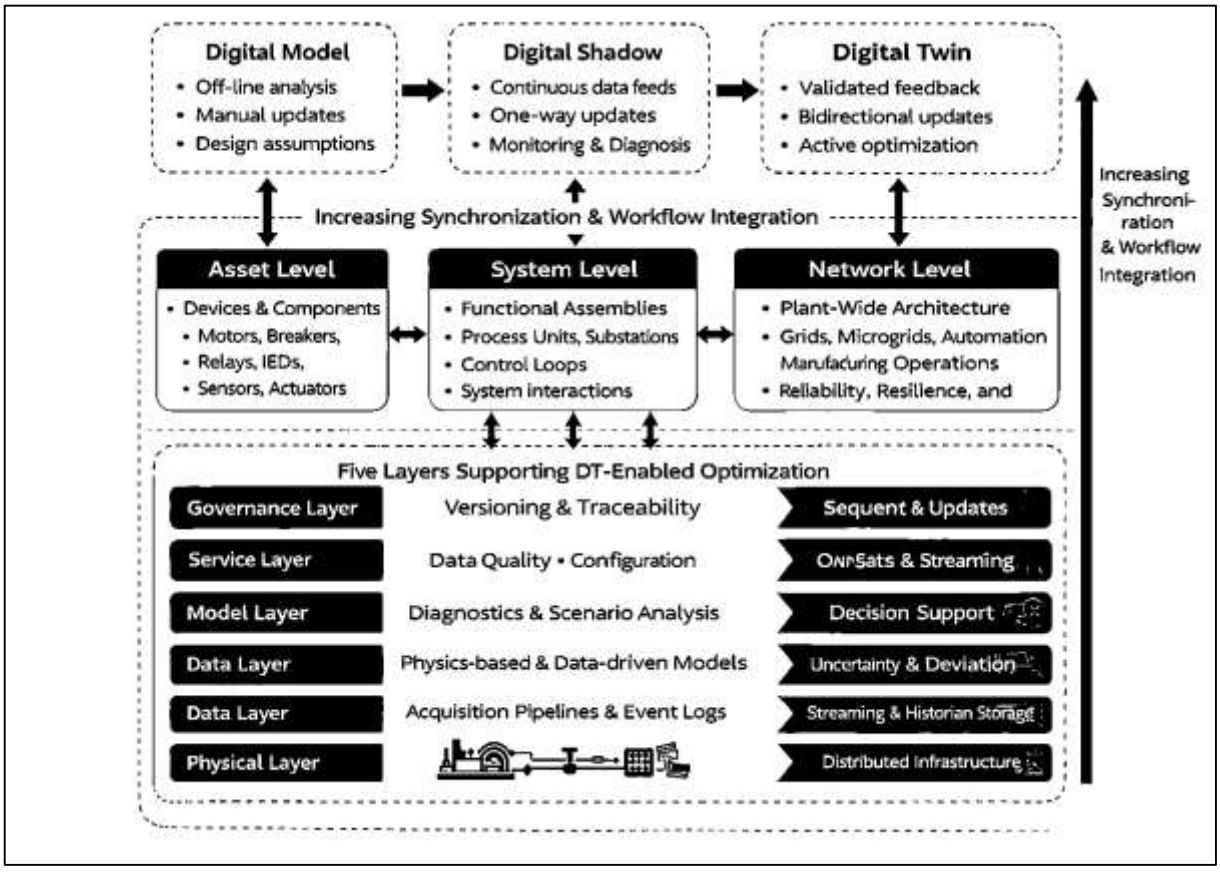
The literature review for Digital Twin–Enabled Optimization of Electrical, Instrumentation, and Control (EIC) Architectures in Smart Manufacturing and Utility-Scale Systems synthesizes research across digital twin engineering, industrial automation, power and utility control systems, instrumentation reliability, and quantitative optimization methods (Yue et al., 2020). Because EIC architectures operate as tightly coupled cyber–physical systems, the review focuses on how prior studies have defined, modeled, measured, and optimized electrical distribution layers, sensing and instrumentation networks, and control and automation hierarchies under operational constraints. The section organizes evidence on how digital twins evolve from static digital models into synchronized, data-driven representations capable of supporting quantitative evaluation of architecture alternatives, including redundancy strategies, communication topologies, control hierarchies, and sensor placement. The review also examines how measurable performance indicators—such as availability, mean time between failures, fault detection coverage, control loop performance indices, latency, data quality scores, and energy efficiency—have been operationalized in both manufacturing and utility-scale contexts (Josifovska et al., 2019). In addition, the literature review consolidates methodological approaches used in quantitative optimization, including simulation-based optimization, mixed-integer formulations for architecture selection, model predictive control for operational decisions, reliability and risk modeling for redundancy and safety, and multi-objective trade-off analysis for cost–performance balancing. Since manufacturing plants and utility-scale systems differ in dynamics, regulatory constraints, and criticality, the review also identifies cross-domain patterns and domain-specific constraints shaping EIC architecture optimization (Eckhart & Ekelhart, 2019). The section concludes by establishing a structured knowledge base that supports model selection, variable operationalization, metric definition, and hypothesis development for the study's quantitative design.

Digital Twin in Cyber–Physical Systems

Digital twin research in cyber–physical systems commonly separate digital models, digital shadows, and digital twins as three related constructs that differ in how tightly a digital representation is connected to a physical system (Park et al., 2021). A digital model is typically treated as a structured representation created for design, verification, or offline analysis, where updates occur manually or intermittently and the representation can remain valid only under assumed boundary conditions. A

digital shadow is generally framed as an automatically updated representation that receives data from the physical system with limited transformation delay, where the physical system "casts" operational reality into the digital environment through continuous data feeds. A digital twin is most often discussed as a higher-coupling construct in which the digital representation is continuously synchronized and capable of supporting operational decision cycles through validated feedback, meaning the representation is not only a mirror but also a controlled analytical counterpart that can guide actions. The literature emphasizes three practical boundaries for separating these constructs: synchronization intensity (how closely the representation matches current physical state), directionality of coupling (one-way updates versus reciprocal operational influence), and update frequency (how regularly state variables refresh relative to process dynamics). These boundaries are not merely definitional; they shape what a study can claim about optimization of electrical, instrumentation, and control architectures (Tao et al., 2019). When synchronization intensity is low, architecture comparisons become reliant on design assumptions and may underrepresent delay-sensitive behaviors such as protective action timing, controller scan cycles, sensor drift, and transient electrical response. When coupling is one-directional, the representation supports monitoring and diagnosis more readily than active optimization of architecture alternatives because the decision loop remains external to the representation. When update frequency is not aligned with system dynamics, measured states can mask instabilities and distort performance measurement, especially in utility-scale systems where fast protection behaviors coexist with slower supervisory functions, and in smart manufacturing where discrete machine events and continuous process variables interact. Across the scholarship, this definitional separation functions as a quality control mechanism for claims about DT-enabled optimization, because optimization requires consistent, measurable alignment between what the system is doing and what the digital representation is evaluating at the same time scale (Suyatinov, 2019).

Figure 3: Digital Twin Framework for Engineering



Literature that treats the digital twin as an optimization instrument describes minimum requirements that move the concept from descriptive representation to quantitative evaluation environment. A recurring requirement is state observability as an operational property rather than an abstract notion: the set of measurements and derived indicators must be sufficient to characterize the conditions that drive the performance outcomes being optimized (Jinnat & Kamrul, 2021; Yildiz et al., 2022). Within EIC architectures, observability extends across electrical states, instrumentation integrity, and control logic execution. Electrical observability can include load behavior at key nodes, voltage and current measurements at relevant points, protective device indications, and disturbances that alter power quality. Instrumentation observability includes signal health, calibration status, measurement drift indicators, noise characteristics, and the completeness of measurement coverage across critical variables. Control observability includes mode and state transitions, alarm and interlock events, controller execution timing, and the mapping between sensed values and actuation outcomes. A second minimum requirement is an update mechanism that ensures the digital representation remains aligned through disciplined time-stamping, alignment across data sources, and consistent handling of missing or delayed information (Saad et al., 2020; Zulqarnain & Subrato, 2021). In both manufacturing and utility systems, data originates from diverse devices with different sampling characteristics, logging rules, and clock accuracy, which makes update mechanisms a foundational architecture attribute rather than a software detail. A third requirement is a validation loop that systematically evaluates how well the digital representation matches observed behavior, records deviation in a measurable way, and supports adjustment of models, assumptions, and data transformation rules (Uddin et al., 2022). The literature places strong emphasis on the credibility of optimization results: comparative evaluation of architecture alternatives is only defensible when model deviation and measurement uncertainty are recognized and managed rather than ignored. In EIC contexts, instrumentation uncertainty and time alignment errors can propagate into state estimation variability, which then changes how control performance and fault response are quantified (Akbar & Sharmin, 2022; Foysal & Subrato, 2022). As a result, DT-enabled optimization is described as dependent on disciplined observability, robust updating, and continual validation, because these features determine whether measured performance differences reflect true architectural advantages or artifacts of data and model mismatch (Biesinger et al., 2019).

A common organizing principle across digital twin studies is the unit of analysis, which determines what the twin represents, what data is required, and what outcomes are meaningful. At the asset level, a twin may focus on devices such as motors, drives, circuit breakers, sensors, transmitters, protective relays, intelligent electronic devices, controllers, and actuators (Al-Ali et al., 2020; Hammad & Mohiul, 2023; Jabed Hasan & Waladur, 2023). Asset-level representations support fine-grained measurement and diagnosis of component behavior, including signal integrity patterns, device response characteristics, local control actions, and localized fault signatures. This level of analysis aligns well with instrumentation-focused optimization decisions such as sensor selection, calibration regimes, measurement quality scoring, and device-level redundancy (Abdul, 2023; Zulqarnain, 2022). At the system level, twins represent integrated functional assemblies such as production line segments, process units, skid packages, substations, protection zones, or coordinated control loop groups. System-level analysis emphasizes interactions among assets: how signals travel through data acquisition layers, how control actions propagate across devices, how network delays influence closed-loop behavior, and how electrical events influence instrumentation and automation states. This level fits architecture decisions such as control hierarchy distribution, network segmentation, gateway placement, and redundancy allocation across critical subsystems (Ding et al., 2019; Rifat & Rebeka, 2023; Kumar, 2023). At the network level, twins represent plant-wide electrical distribution and automation architectures, microgrids, grid segments, multi-substation automation landscapes, or multi-site manufacturing operations. Network-level analysis focuses on system-wide outcomes such as availability, reliability, disturbance containment, and coordinated restoration behavior, while also accounting for the fact that distributed architectures can introduce complex dependencies that only become visible when the boundary includes multiple subsystems. The literature presents these units of analysis as nested rather than competing, emphasizing that EIC optimization requires matching the twin boundary to the

decision boundary. Sensor placement decisions can be evaluated at asset and system levels; protection coordination and redundancy strategies demand system and network perspectives; communication and semantic consistency issues become most visible at system and network levels where multi-source integration occurs (Masud & Hossain, 2024; Zulqarnain & Subrato, 2023). This layered approach supports comparative reasoning across smart manufacturing and utility-scale contexts because both domains rely on hierarchical asset-system-network organization even though their operational rhythms and criticality profiles differ (Park et al., 2020).

Digital twin scholarship that addresses EIC-relevant applications frequently describes a layered architecture that supports consistent flow from physical signals to quantified evaluations, while keeping the representation auditable and repeatable (Balta et al., 2023; Md & Praveen, 2024; Nahid & Bhuya, 2024). The physical layer includes electrical distribution elements, sensing devices, actuators, controllers, and embedded communication interfaces that generate observable signals and execute actions. The data layer includes acquisition pipelines, time-stamping practices, historian storage, streaming mechanisms, and event logs that preserve operational context, including alarms, trips, mode changes, and setpoint adjustments. The model layer combines physics-based representations of electrical and process behaviors with data-driven components that capture empirical patterns, anomalies, and operational variability that are not fully represented through first-principles models alone (Newaz & Jahidul, 2024; Akbar, 2024). The service layer operationalizes the twin into diagnostics, scenario evaluation, optimization routines, and decision support outputs that translate system states into measurable performance indicators relevant to architecture decisions. The governance layer maintains configuration versioning, traceability of model assumptions, semantic consistency of tags and asset identifiers, and quality scoring for data streams and model outputs (Rabiul & Alam, 2024; Kumar, 2024). Governance is repeatedly positioned as essential in EIC settings because architecture performance is sensitive to small configuration changes: a sensor recalibration alters measurement integrity, a control logic revision changes actuation behavior, a relay setting update shifts protection response, and a network reconfiguration changes communication delay profiles (Fett et al., 2023; Sai Praveen, 2024; Azam & Amin, 2024). Quantitative emphasis in this layered framing is typically expressed through measurable constructs such as synchronization lag described in time units, update rate described by cycles of refresh over time, model deviation summarized through error aggregation measures, and state estimation confidence described through interval-based uncertainty characterization. These constructs allow studies to evaluate digital twin maturity and optimization credibility using observable properties rather than labels. Across manufacturing and utility-scale systems, the layered architecture perspective provides a structured explanation for how DT-enabled optimization becomes possible: the physical layer produces the truth basis, the data layer preserves and aligns it, the model layer interprets it, the service layer evaluates alternatives, and the governance layer ensures that results remain traceable and comparable when architectures change over operational lifecycles (Zhang et al., 2019).

Smart Manufacturing and Utility-Scale Systems

Electrical architecture optimization in smart manufacturing and utility-scale systems is commonly treated in the literature as a structured design-and-evaluation problem in which architecture choices determine how safely, efficiently, and reliably electrical energy is delivered to loads and mission-critical functions (Samad & Bienert, 2020). Across industrial plants, electrical architectures provide the backbone that powers production assets, automation platforms, and safety-related systems, while in utility-scale contexts electrical architectures coordinate generation, transmission, distribution, and protection functions that collectively sustain public and industrial service continuity. A recurring theme in research is that architecture optimization begins with explicit representation of power distribution topology as a categorical design choice that shapes flow paths, fault isolation capability, maintenance flexibility, and restoration behavior. Radial arrangements are discussed as comparatively simple and cost-sensitive, while ring and meshed arrangements are treated as architectures that introduce alternative supply paths and can reduce service interruption exposure when faults occur (Smith et al., 2019). In smart manufacturing, topology considerations extend beyond feeders and buses to include how electrical zones align with production cells, process criticality, and automation boundaries, since electrical segmentation can influence both downtime propagation and maintenance

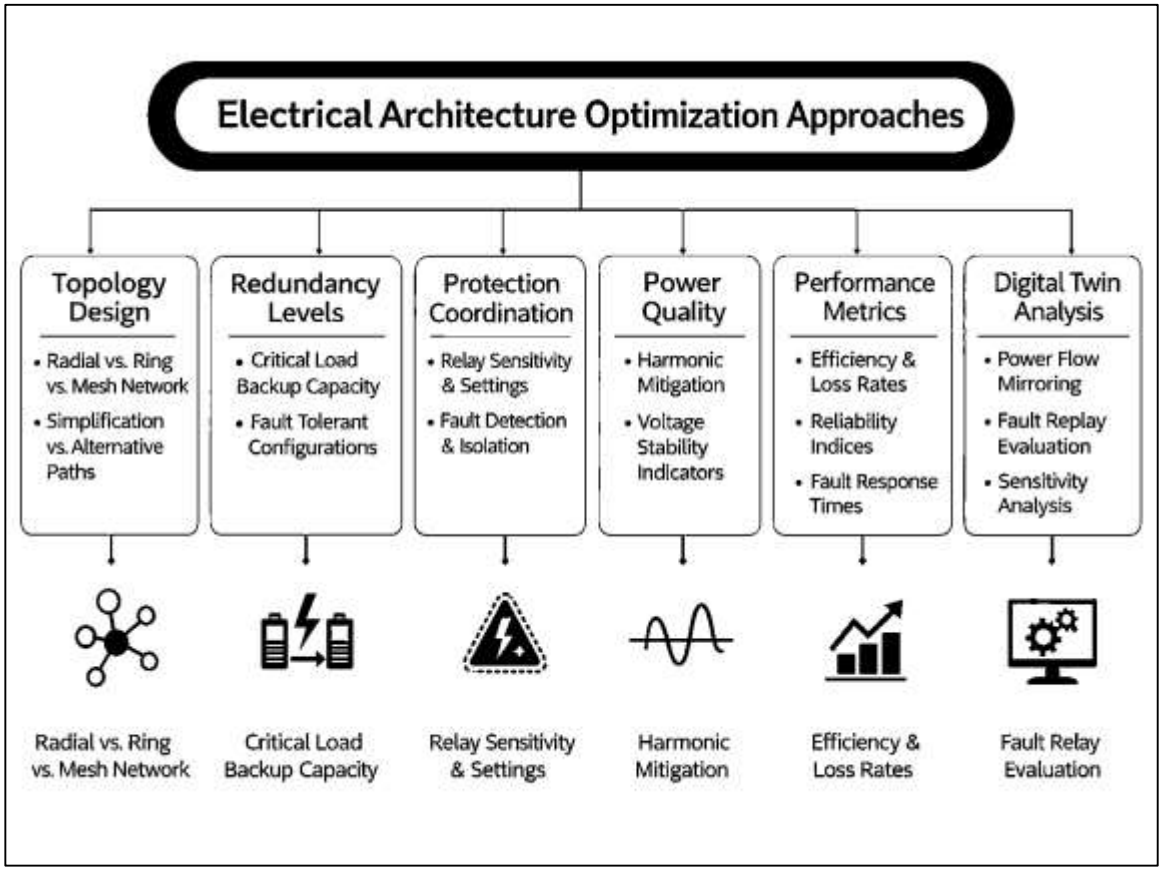
isolation. In utility-scale systems, topology is often framed through the interaction between network structure, load variability, and operational switching capability, where reconfiguration decisions may influence constraint management and service reliability. Literature also positions redundancy level as a discrete architecture variable that translates operational criticality into engineered availability. Redundancy is described through structured capacity arrangements that determine whether critical loads remain supplied when a component fails, and the choice of redundancy is treated as a measurable trade-off among capital cost, operational risk, and maintainability. These architecture decisions are repeatedly linked to quantifiable outcomes because topology and redundancy shape how disturbances travel through the system, how rapidly isolation can occur, and how effectively loads can be restored (Confrey et al., 2019). As a result, electrical architecture optimization is presented not as a single-device improvement activity but as a system-level design discipline where categorical and discrete architectural choices govern performance boundaries for the entire EIC ecosystem.

Studies addressing quantitative design variables frequently highlight protective coordination settings as a major continuous decision space that can significantly influence fault containment and equipment protection outcomes (Jaramillo-Leon et al., 2023). Protective coordination is typically discussed as a structured alignment of protective devices such that faults are cleared by the most appropriate device with adequate speed, while ensuring upstream devices remain stable and selective. The literature treats protective coordination settings as tunable parameters that must balance sensitivity, speed, and selectivity under varying operating conditions, including changing load levels, distributed generation effects, motor starting currents, and evolving short-circuit contributions. In manufacturing, protective coordination is linked to production continuity because miscoordination can trigger unnecessary trips that halt production lines, disrupt control systems, and increase restart losses. In utility-scale systems, coordination is associated with broader consequences, including customer outages and cascading interruptions when protection does not isolate faults as intended (Starke et al., 2019). Research also emphasizes harmonic mitigation and power quality parameters as measurable outcomes and design variables that can be influenced through architecture choices and conditioning equipment. Harmonics, voltage distortion, flicker, and unbalance are presented as performance dimensions that affect drives, instrumentation accuracy, controller stability, and equipment lifetime. In smart manufacturing, the growth of power electronics-based drives and converters intensifies attention to power quality, because sensitive instrumentation and control platforms can be affected by electrical noise and distortion. In utility-scale systems, large renewable plants and converter-based interfaces are often associated with power quality considerations that must be managed across interconnection points and grid codes (Kalantar-Neyestanaki & Cherkaoui, 2021). The literature integrates these themes by framing architecture optimization as a multi-variable problem: topology and redundancy provide structural resilience, protective coordination settings define fault-clearing behavior, and harmonic mitigation strategies influence steady-state quality and equipment interaction stability. This integrated view positions electrical architecture as a measurable performance system rather than a static one-time design artifact.

Electrical performance metrics reported in prior work tend to cluster around efficiency-related indicators, reliability indicators, and protection response indicators, with emphasis on outcomes that can be measured consistently across time windows and operating conditions (Schleifer et al., 2021). Efficiency is frequently represented through measurable energy loss quantities and system efficiency rates, where losses are treated as a function of loading, conductor and transformer characteristics, and architecture-induced flow paths. In manufacturing, this perspective is often connected to operational cost control because losses accumulate across continuous production and can be amplified by suboptimal distribution layouts or poor power factor and harmonic conditions. In utility-scale systems, loss evaluation is commonly treated as both an economic and capacity management problem, because losses affect overall energy delivery efficiency and constrain network loading. Voltage deviation and frequency stability indicators are also presented as critical metrics, especially where sensitive equipment and protection systems rely on stable electrical conditions. Reliability metrics differ by domain but share a common purpose: quantify service continuity. Utility-scale research commonly uses standardized interruption-oriented indices to measure customer impact and system service

performance, whereas manufacturing-oriented work emphasizes downtime duration, availability percentages, and production interruption frequency because plant output is directly affected by electrical service discontinuity (Shapsough & Zualkernan, 2019). Protection and fault-related metrics receive sustained attention, including fault response time, selectivity performance, and protection misoperation rates, because these indicators translate architecture decisions into real consequences during abnormal conditions. Fault response time is commonly treated as a reflection of protection coordination quality, breaker performance, communication support for protection schemes, and the suitability of settings under variable system conditions. Selectivity performance describes whether the system isolates only the faulted section while maintaining supply to healthy sections, and misoperation rates quantify incorrect or unnecessary protective actions that create avoidable interruptions. Across the literature, these metrics serve as the quantitative bridge between design variables (topology, redundancy, protection settings, conditioning devices) and operational outcomes (cost, continuity, safety, equipment stress), enabling comparative evaluation of architecture options using measurable evidence rather than descriptive preference (Wang et al., 2019).

Figure 4: Electrical Architecture Optimization Framework



Digital twin use cases for electrical optimization are frequently organized around three major analytical functions: operational mirroring, event-based evaluation, and sensitivity-driven architecture comparison. First, real-time power flow mirroring and constraint checking are described as mechanisms for keeping a digital representation aligned with actual operating states so that electrical constraints, loading conditions, and operational limits can be monitored with higher contextual integrity than isolated measurements (Zafar et al., 2020). In manufacturing environments, mirroring is commonly presented as an approach to unify electrical states with production context, enabling evaluation of how line states, machine utilization, and electrical loading interact. In utility-scale systems, mirroring is described as a means to enhance situational awareness by aligning measurements with network state representations that support constraint monitoring and operational switching decisions. Second, fault scenario replay and contingency testing are treated as high-value use cases because electrical systems are defined by how they behave under abnormal events as much as under

normal operation. Replay-based evaluation allows the architecture and its protection logic to be assessed against realistic disturbances, enabling comparison of how different topologies, redundancy choices, and coordination settings influence fault isolation, restoration speed, and misoperation exposure. This use case is also discussed as a method for identifying patterns that are hard to observe in real time because faults are infrequent yet consequential (Abid et al., 2021). Third, parameter sensitivity analysis is frequently described as a structured method to link architecture choices to stability and loss outcomes by evaluating how small changes in settings, load distributions, or configuration assumptions shift measurable performance indicators. Sensitivity analysis supports prioritization by showing which architecture variables exert the largest influence on losses, voltage deviation, interruption exposure, and protection response behavior. Across these use cases, the literature treats digital twins as an enabling environment for quantitative comparison because the same measurable metrics used in operational reporting can be applied to evaluate alternative architecture configurations under consistent conditions. This produces a coherent evaluation pathway where structural decisions, tunable settings, and measured performance outcomes can be connected through repeatable analytical workflows grounded in observed system behavior rather than speculative reasoning (Eltamaly et al., 2020).

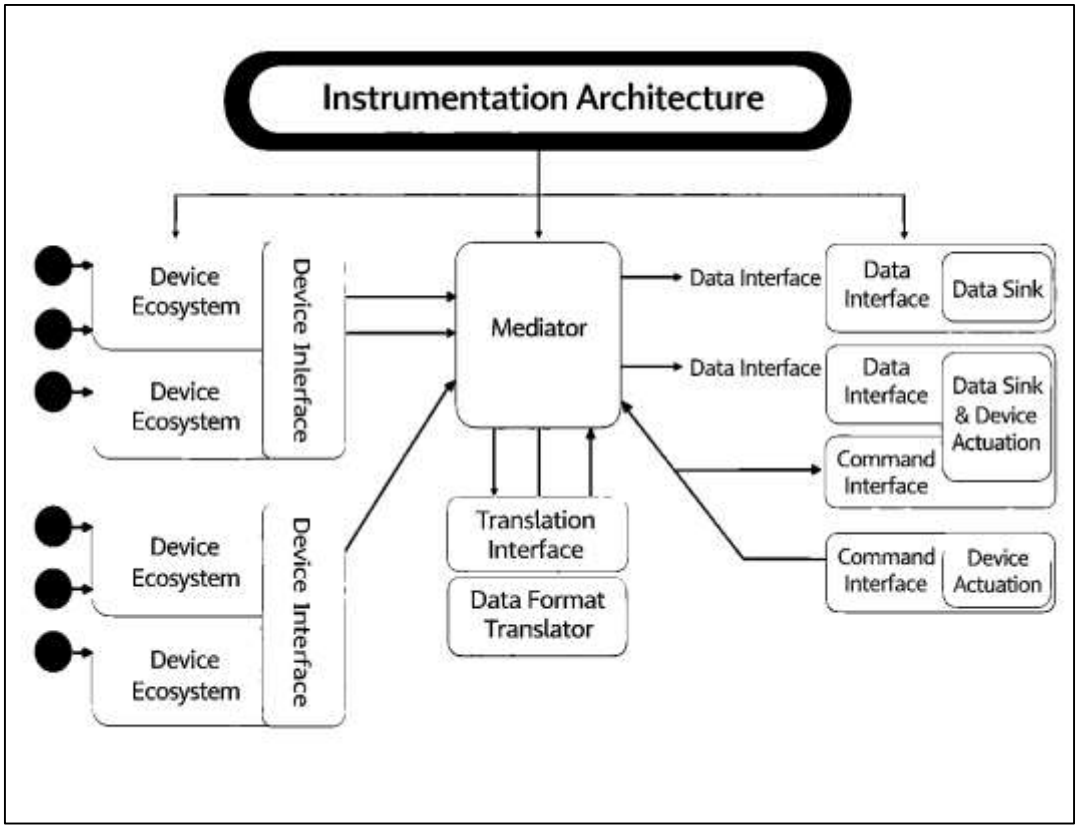
Instrumentation Architecture and Diagnostic Coverage

Instrumentation architecture is treated across industrial, process, and cyber–physical systems literature as the structural foundation that determines what a system can know about itself, how reliably it can know it, and how quickly that knowledge can be converted into action (Ferlini et al., 2020). In smart manufacturing and utility-scale environments, instrumentation is not only a collection of sensors; it is an engineered network of measurement points, signal conditioning, data acquisition, tagging, synchronization, calibration practices, and diagnostic logic that collectively produces operational observability. The literature repeatedly emphasizes that instrumentation architecture influences both operational performance and the credibility of analytics, because every higher-level function—state estimation, control tuning, fault diagnosis, and digital twin synchronization—depends on measurement integrity. Studies commonly operationalize instrumentation design variables beginning with sensor density, expressed as the number of sensors per asset, per process area, or per critical node category. Higher density is associated in research with improved fault localization and improved estimation fidelity, while also introducing higher integration complexity, higher calibration burden, and higher risk of inconsistent semantics across signal sets when governance is weak (Lin et al., 2022). A second variable is sensor placement strategy, where research contrasts coverage focused on critical nodes, boundary measurements, and high-variability zones against uniform distribution across assets. Placement strategy is described as a determinant of observability quality because certain variables carry disproportionate information about system states and fault propagation pathways. In both manufacturing and utilities, literature characterizes the placement problem as a structural decision that shapes diagnostic reach and response speed. Additional design variables frequently treated as architecture-level decisions include calibration interval and drift behavior, because measurement stability over time is central to maintaining trustworthy baselines for monitoring and control. Calibration strategy is discussed as a trade-off between resource effort and measurement credibility, particularly where harsh environments, vibration, temperature variation, and electrical noise contribute to drift. The literature also treats sampling characteristics—sampling rate, signal resolution, and noise characteristics—as architecture drivers rather than device properties because they shape data granularity and the ability to detect anomalies, transients, and control-relevant changes (Hukerikar & Saxena, 2022). Together, these variables define the measurable capacity of instrumentation to produce consistent and decision-grade visibility across the EIC environment.

Measurement quality metrics reported in prior research emphasize completeness, validity, alignment, uncertainty characterization, and detection performance as core indicators of instrumentation integrity (Wang et al., 2021). Data completeness is commonly described through missingness rates, gaps, and dropout patterns across sensors and time windows, with the literature noting that missing data is rarely random in industrial systems because it may correlate with device faults, network congestion, maintenance actions, or power disturbances. Data validity is often framed as the proportion of measurements within plausible operating bounds, including adherence to physical constraints,

engineering limits, and consistency rules across redundant measurements. Timestamp alignment integrity is frequently discussed in systems where multiple acquisition pathways exist, since misalignment introduces artificial phase shifts and can misrepresent causality between measurement changes and control actions. In utility-scale systems, time alignment is critical for event reconstruction and disturbance analysis, while in manufacturing it influences the interpretability of causal sequences between machine states, process variables, and controller actions. The literature also emphasizes measurement uncertainty as a measurable attribute that determines confidence in state estimates and diagnostic classifications (Sundararajan et al., 2019). Uncertainty is discussed through dispersion characteristics and interval-based confidence descriptors, with special attention to how uncertainty changes under sensor drift, environmental conditions, and calibration quality. Diagnostic performance metrics are also widely used, including fault detection coverage, false alarm behavior, and detection delay. Fault detection coverage is treated as a system property that depends on what is measured, where it is measured, how frequently measurements arrive, and whether measurement noise obscure's weak fault signatures. False alarms are described as particularly harmful in operational settings because repeated nuisance signals degrade trust, increase response fatigue, and can cause operators to ignore genuine anomalies. Detection delay is treated as a measurable time-to-detection outcome that is shaped by sampling granularity, filtering strategies, and signal-to-noise characteristics (Boyle et al., 2020). Across the literature, these metrics function as a quantitative bridge connecting instrumentation architecture decisions to operational reliability, safety response quality, and the stability of control systems.

Figure 5: Instrumentation Architecture Optimization Framework



Within digital twin optimization literature, instrumentation architecture is repeatedly positioned as a primary lever for improving observability and enabling credible optimization workflows. A synchronized twin requires measurement streams that are temporally aligned, semantically consistent, and sufficiently informative to estimate the evolving system state (Ehrenberg et al., 2019). Research frequently describes twin-driven sensor placement optimization as an approach in which candidate sensor configurations are evaluated based on their contribution to system observability and diagnostic

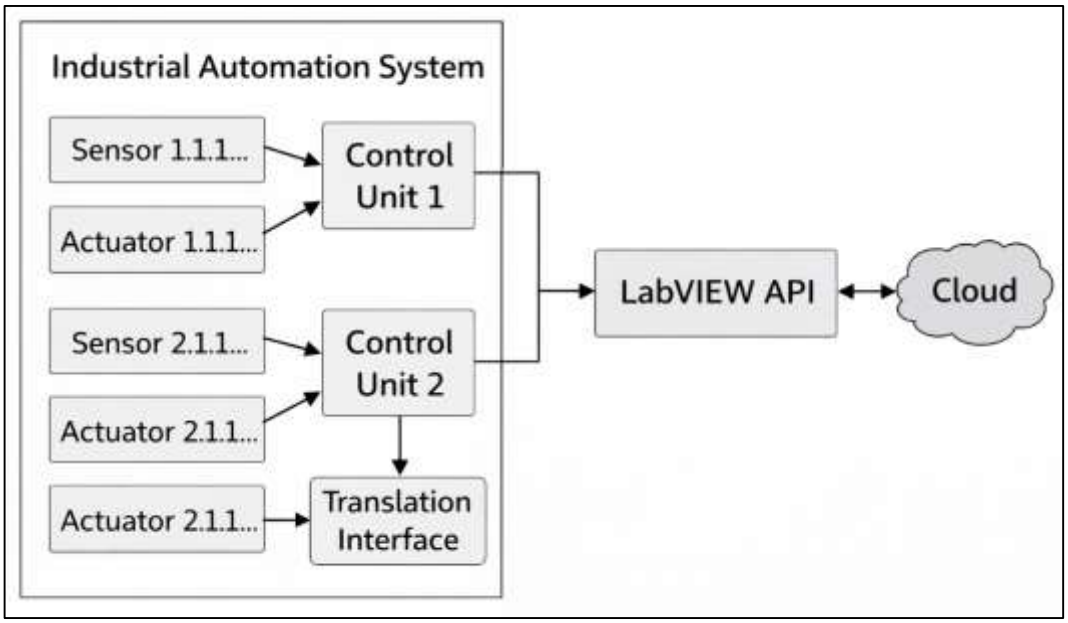
power, using digital representations to compare alternatives without disrupting physical operations. This framing treats instrumentation decisions as optimization variables and measurement quality metrics as objective indicators of success, supporting structured comparison of critical-node concentration strategies versus more uniform sensing schemes. Literature also emphasizes that instrumentation architecture interacts strongly with control architecture, because control decisions depend on measurement integrity, and measurement anomalies can propagate into unstable control actions or incorrect protective behavior. For this reason, digital twin studies often integrate instrumentation quality scoring into synchronization logic so that questionable signals are flagged, weighted, or isolated based on their integrity characteristics (Deyati et al., 2023). Another recurring theme is the integration of statistical process monitoring into instrumentation-driven optimization, where control chart logic, multivariate monitoring, and anomaly detection frameworks are used to extract actionable insights from sensor networks. These methods are described as complementary to twins because they provide systematic ways to detect drift, outliers, and early fault signatures that affect the twin's accuracy and the reliability of optimization recommendations. In both manufacturing and utility-scale contexts, multivariate monitoring is presented as valuable where variables are coupled and single-signal thresholds are insufficient. The literature also highlights that instrumentation optimization often involves balancing informational benefit against complexity cost by evaluating how additional sensors improve detection coverage or reduce uncertainty while considering maintenance and calibration burden. In this way, digital twin–enabled instrumentation optimization is framed as a measurable process that links architectural decisions to observable outcomes, using repeatable comparisons grounded in operational data behavior (Bolanowski et al., 2023).

Control Architecture Optimization

Control architecture optimization literature in smart manufacturing and utility-scale systems consistently frames control as a layered cyber–physical mechanism through which measurement is transformed into coordinated action, and it treats architecture as the arrangement of decision authority, timing discipline, safety segregation, and communication dependencies across layers (Minaeva et al., 2020). In manufacturing, control layers are typically described through field control implemented on programmable controllers and embedded devices, supervisory control implemented through distributed control systems or supervisory monitoring platforms, and enterprise integration layers that connect production decisions with planning, quality, and asset management functions. In utilities, parallel layering appears through intelligent electronic devices and protection controllers at the field level, supervisory energy management and control center systems at the supervisory level, and enterprise layers that manage asset health, market coordination, and operational planning. The literature emphasizes that these layers exist because control problems occur on different time scales and require different levels of local autonomy versus global coordination. Field-level control is often associated with fast deterministic execution and direct actuation; supervisory control is associated with coordination, monitoring, and setpoint management; enterprise integration is associated with optimization of broader objectives such as efficiency, throughput, reliability, and asset utilization. Research highlights that optimization becomes an architectural question when control tasks are distributed across devices and layers with different timing guarantees, computational capabilities, and failure modes (X. Li et al., 2020). This comparative view across manufacturing and utilities shows that the same structural themes recur even when application goals differ: both domains manage rapid protective or regulatory actions locally while coordinating system objectives through supervisory decision cycles. This context also motivates categorical treatment of control architectures—centralized, distributed, and hierarchical—as predictors of measurable performance differences. Centralized control is frequently associated with globally informed decision-making and consistent policy application, while distributed control is associated with local responsiveness and reduced communication dependency. Hierarchical architectures are often positioned as a compromise that assigns fast safety and regulatory actions to local layers while coordinating slower optimization at upper layers. Literature synthesis also emphasizes safety-related control segregation as a defining architecture feature, where safety instrumented functions are kept logically and often physically separated from basic process control to preserve predictable behavior during abnormal events. This segregation is treated as an architecture determinant that shapes how faults propagate and how the

system behaves under both process disturbances and control failures (Shin et al., 2019).
Quantitative control performance measures reported across studies emphasize tracking quality, transient response, stability characteristics, interaction behavior, and timing fidelity as the core measurable outputs through which architecture alternatives are compared (Chen et al., 2020). Tracking quality is commonly operationalized as the magnitude and persistence of deviation between desired and measured values over time, interpreted as the control system's ability to regulate processes and maintain setpoints under disturbances. Transient response is evaluated through observable overshoot behavior and the time required for the controlled variable to reach and remain within a practical tolerance band after a change, because these characteristics determine product quality consistency in manufacturing and stability of operational targets in utilities. Stability is treated as a measurable property that reflects the control system's resilience to disturbances and modeling error, and it is frequently discussed as sensitive to delays, noise, actuator limits, and loop interactions. Loop interaction indices and multivariable coupling measures are repeatedly emphasized in complex plants and grid-related controls because multiple loops interact through shared physical pathways; architecture decisions about loop pairing, decoupling strategies, and coordination policies can change the degree to which one loop's action produces unintended effects in another. Timing measures are treated as decisive architecture indicators in both domains (Y. Wang et al., 2022). Control execution jitter captures variability in execution timing that can degrade repeatability, scan time reflects the periodicity and workload constraints of controller cycles, and network-induced delay describes the effect of communication latency on the timeliness of measurement arrival and actuation dispatch. Literature shows that timing degradation can transform otherwise stable designs into oscillatory or sluggish behavior, particularly in distributed architectures where communication links become part of the feedback path. In manufacturing, timing variation can cause quality variability, increased scrap, and unstable machine coordination in high-speed lines. In utilities, timing variability affects coordinated control actions and can influence protection and automation behavior when communication-assisted schemes are involved. The recurring synthesis is that control architecture optimization is meaningful when performance is measured through a combined lens of tracking, transient behavior, stability robustness, interaction sensitivity, and timing integrity, because these categories capture how well the control system performs under realistic operational variability (Mohajer et al., 2022).

Figure 6: Control Architecture Optimization Framework



Digital twin–enabled control optimization literature positions virtual representations as a means to evaluate and refine control architecture choices through repeatable, data-aligned experiments rather

than trial-and-error changes applied directly on operating systems (Amini et al., 2020). A prominent use case is virtual commissioning, where control logic and sequencing are tested against realistic process representations before or alongside deployment, enabling measurable validation of interlocks, state transitions, alarm logic, and coordinated machine behavior. In this framing, validation metrics are tied to measurable outcomes such as the proportion of test scenarios executed without violations, the rate of detected logic conflicts, the frequency of abnormal state transitions, and the extent to which simulated process responses match observed behavior during controlled tests. Digital twin studies also highlight model-based tuning using synchronized process states, where tuning is grounded in operational data streams aligned with the twin's state representation so that tuning changes can be evaluated against realistic disturbance profiles and operating regimes. This approach supports quantitative comparison of tuning strategies by measuring changes in tracking quality, transient response, and interaction sensitivity under consistent scenario sets (Ma et al., 2019). Literature also describes comparative evaluation of control allocation strategies, particularly the trade-off between edge-local decision-making and centrally coordinated decision-making. Edge-local allocation is often evaluated for responsiveness and reduced reliance on communication stability, while central allocation is evaluated for global coordination and consistent constraint management. Hierarchical approaches are evaluated based on whether they preserve deterministic local regulation while enabling higher-level optimization to coordinate resources across systems. Across these studies, digital twins are positioned as enabling consistent evaluation across architecture alternatives because the same operational data streams and scenario libraries can be used to compare distributed, centralized, and hierarchical patterns under matched conditions (Sun et al., 2019). This enables control architecture optimization to be expressed as a measurable, evidence-based selection of where control authority resides, how timing is maintained, how safety segregation is enforced, and how performance indices respond to structural control decisions in both smart manufacturing and utility-scale systems.

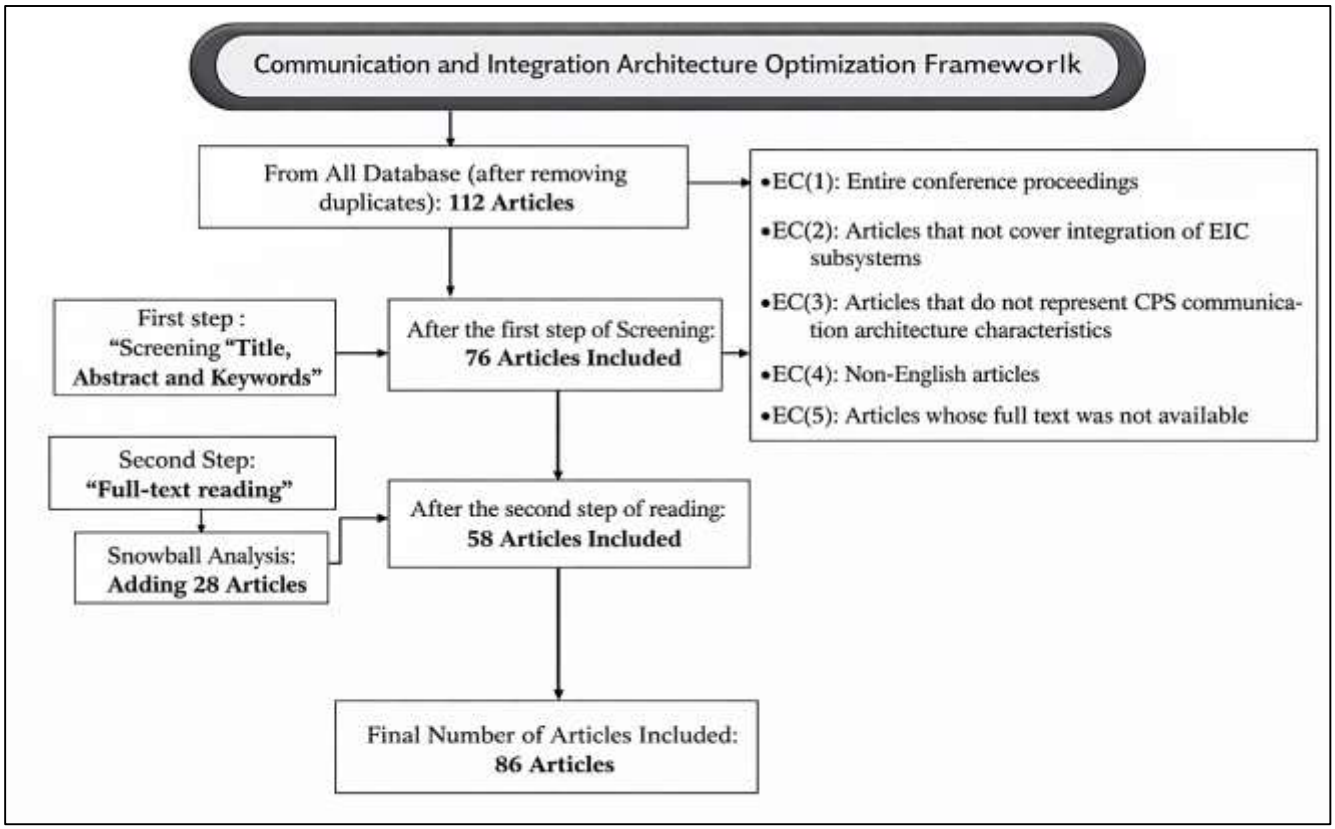
A further synthesized theme in the literature is that control architecture optimization is not limited to improving single-loop regulation but extends to managing the broader socio-technical environment of operations, including maintainability, diagnosability, and auditability of control changes. Control systems in manufacturing and utilities operate under frequent modifications driven by product changes, equipment upgrades, regulatory requirements, and operational learning (Ye et al., 2019). Digital twin frameworks are discussed as particularly relevant for managing this change density because they allow control strategies to be tested and measured within a controlled representation that preserves configuration context. In this view, the governance of control logic versions, the traceability of tuning changes, and the repeatability of validation tests become part of architecture quality because they determine whether performance can be sustained as the system evolves. This is especially relevant where safety instrumented functions require strict separation and disciplined proof of behavior under abnormal conditions, and where protection and automation functions must be predictable under disturbances (Yong Wang et al., 2023). The literature links this governance dimension to measurable operational effects through patterns such as reduction in nuisance alarms, reduction in unplanned interventions due to unstable tuning, reduction in commissioning time, and improved consistency of performance indices across operating regimes. Another recurring emphasis is that control architectures are evaluated not only on average performance but on performance variability, including how often performance deviates beyond acceptable bands under normal fluctuations. Timing measures, interaction indices, and tracking measures are therefore discussed as distributional properties across operating conditions rather than single-point values. This supports the framing of control optimization as an empirical, data-driven discipline where digital twins supply a repeatable evaluation space and architecture variables define how well the control system maintains stable, safe, and efficient operation across realistic variability in manufacturing and utility-scale environments (Nguyen et al., 2019).

Communication and Integration Architecture

Communication and integration architecture is treated in the literature as the connective tissue that binds electrical, instrumentation, and control subsystems into a coherent cyber–physical system, and it is frequently framed as a primary determinant of whether smart manufacturing plants and utility-scale infrastructures can achieve reliable observability and controllability (Hardjono et al., 2019). In both domains, the communication fabric must carry time-sensitive control and protection signals, high-

volume measurement streams, and event logs while preserving timing discipline and semantic meaning across heterogeneous devices. Researchers commonly conceptualize communication quality through quantifiable variables such as latency, jitter, packet loss, throughput capacity, and time synchronization accuracy, because these variables shape the integrity of feedback loops and the interpretability of event sequences. Latency is treated as a critical property because it directly affects the timeliness of measurements arriving at controllers and decisions reaching actuators, while jitter is treated as a destabilizing factor because it introduces variability that can degrade repeatability even when average latency is acceptable. Packet loss is discussed as a source of hidden uncertainty, as intermittent gaps can mimic sensor faults or process disturbances, and it can trigger retransmission patterns that increase effective delay. Throughput is positioned as a capacity constraint that becomes more salient as systems integrate higher-resolution sensing, condition monitoring, and event-rich logs, requiring architecture decisions that separate deterministic control traffic from best-effort data streams (Sharma et al., 2023). Time synchronization error is highlighted as a cross-cutting issue because misaligned clocks distort causality reconstruction, hinder disturbance analysis, and degrade the alignment between distributed measurements and control actions. The literature also treats topology decisions—such as star, ring, and mesh arrangements—and the number of segments and gateways as architecture-level predictors of performance because they influence failure containment, congestion patterns, and the ability to enforce security boundaries without undermining operational requirements. In manufacturing, these factors are often examined in the context of production cell coordination, high-speed machine control, and integration between operational and enterprise systems, while in utilities they are examined in relation to protection coordination, substation automation traffic, and wide-area monitoring environments (Xue et al., 2022). Across both contexts, communication and integration architecture is repeatedly presented as a measurable performance system where timing, reliability, and alignment features define the operational envelope for safe and efficient EIC behavior.

Figure 7: Communication and Integration Architecture Framework



A major strand of literature focuses on integration readiness as a semantic and governance problem rather than solely a connectivity problem, emphasizing that data without consistent meaning cannot support reliable control analytics or digital twin synchronization (Y. Li et al., 2020). Tagging and

naming consistency is frequently treated as an operationalized indicator of integration maturity because inconsistent labels, ambiguous identifiers, and non-standard naming conventions create mapping errors that propagate through historians, analytics, and control applications. Studies emphasize that tag consistency affects not only reporting convenience but also the correctness of automated reasoning in condition monitoring, fault diagnosis, and optimization workflows that rely on signal relationships and asset context. Semantic interoperability measures are often discussed in terms of mapping completeness between source systems and target models and the extent to which schema coverage represents the required attributes of assets and processes. In EIC environments, schema coverage is not limited to process variables; it must include configuration context such as measurement units, calibration parameters, engineering limits, device roles, control modes, and state-transition semantics. Literature also highlights event logging completeness and traceability metrics as critical to integration quality because event logs are the primary artifacts for diagnosing abnormal behavior, validating control logic, and reconstructing disturbances (Lu & Asghar, 2020). Logging completeness is discussed as the proportion of relevant events captured with sufficient detail and consistent time alignment, and traceability is discussed as the ability to link events across layers, such as linking a protective trip to upstream disturbance indicators, associated controller state changes, and preceding sensor anomalies. In both manufacturing and utility-scale systems, the literature describes integration failures as frequently rooted in semantic inconsistency and incomplete logging rather than bandwidth limits, because systems can be well-connected yet analytically unreliable when signal meaning and event context are not preserved. This semantic framing aligns with the increasing complexity of multi-vendor environments where gateways and middleware translate protocols and data models, creating additional opportunities for loss of meaning when mappings are incomplete (Cavalcanti et al., 2023). Across studies, integration readiness is therefore presented as a measurable architecture quality dimension that can be assessed using consistency scores, mapping completeness indicators, coverage measures, and traceability checks, all of which influence the reliability of downstream optimization and decision support functions.

Methods Used for EIC Architecture Decision-Making

Quantitative optimization methods used for electrical, instrumentation, and control architecture decision-making are presented in the literature as a structured pathway for translating complex engineering trade-offs into measurable selection rules (Maureira et al., 2021). Across smart manufacturing and utility-scale systems, optimization problems are commonly framed around the selection and configuration of architecture features that shape energy efficiency, reliability, safety integrity, and cost performance. Studies frequently classify optimization structures as either single-objective or multi-objective, where the former targets a dominant performance measure such as loss reduction or downtime minimization and the latter balances competing objectives such as cost, risk exposure, reliability, power quality, and operational stability. The literature treats this distinction as more than a modeling preference because EIC architectures rarely operate under a single performance criterion; decisions such as redundancy allocation, protection coordination settings, and communication segmentation inherently trade capital cost and complexity against measurable reductions in interruption exposure and fault propagation (Shi et al., 2023). Constraints are reported as central components of architecture optimization, typically including safety limits that define allowable operating ranges, regulatory thresholds governing performance and reporting requirements, and capacity and timing constraints that reflect physical limitations and control determinism requirements. In manufacturing contexts, constraints often relate to production continuity boundaries, permissible process variable ranges, and actuator saturation or timing restrictions imposed by controller scan cycles and network delay. In utility-scale contexts, constraints are commonly framed in terms of secure operation boundaries, voltage and frequency tolerances, thermal loading limits, and protection and automation timing expectations. Another recurring synthesis in the literature is the mixed nature of architecture decisions, where discrete choices such as topology category, redundancy class, and gateway count interact with continuous choices such as protection and control parameter settings, sampling configurations, and tuning thresholds. This duality is frequently discussed as an inherent characteristic of EIC architecture optimization because practical design decisions involve both structural selection and parameter refinement. As a result, the literature positions quantitative

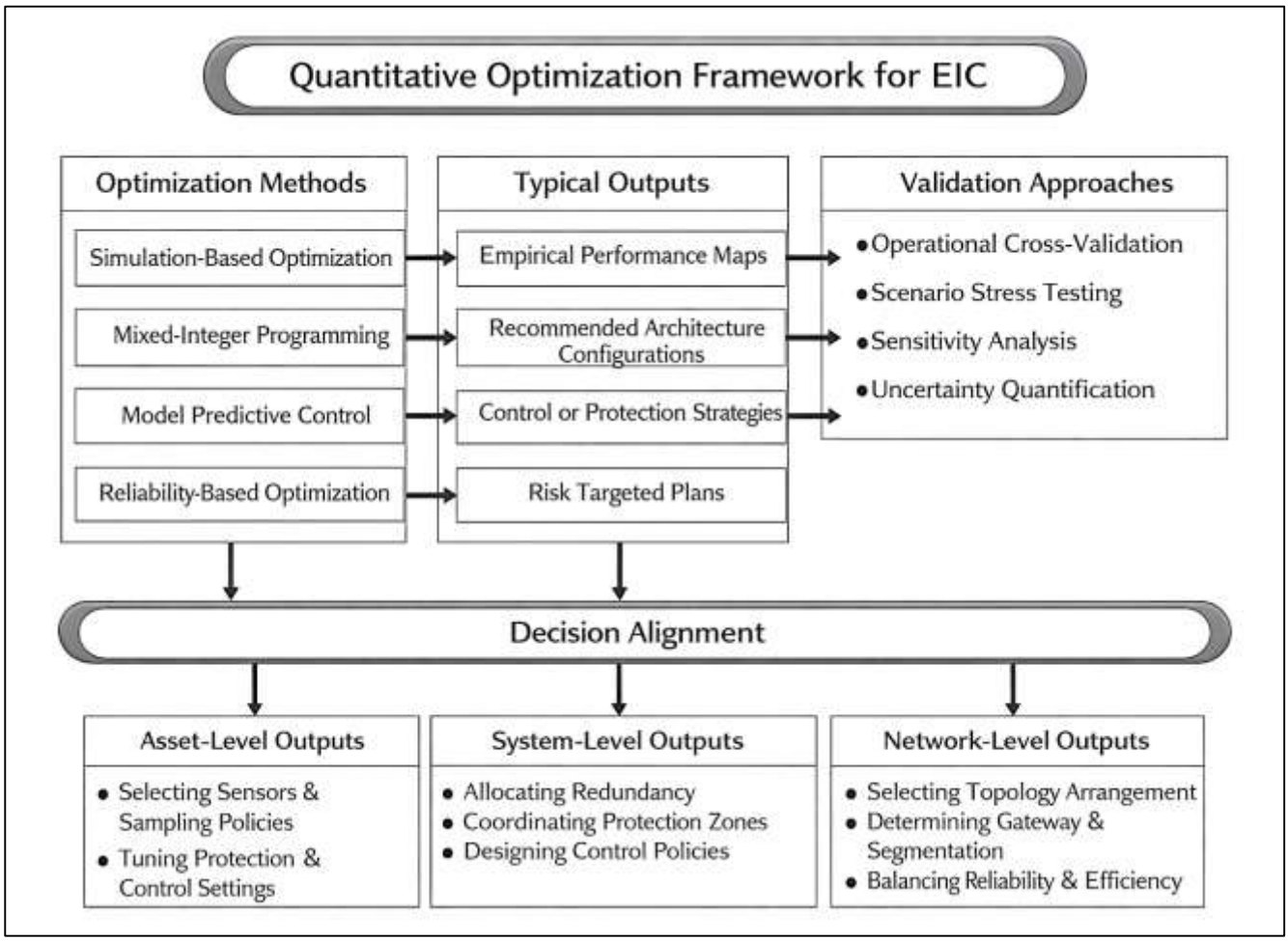
optimization as a necessary tool for architecture decision-making because it provides consistent procedures for comparing alternatives under shared constraints and measurable performance criteria rather than relying on expert judgment alone (Li et al., 2022).

Simulation-based optimization is widely described as a pragmatic approach for EIC architectures because many relevant performance behaviors arise from complex interactions that are difficult to represent through simplified analytical relationships alone. In manufacturing, simulation-based approaches often rely on integrated process, equipment, and control representations that reproduce state transitions, control actions, and disturbance patterns, enabling performance assessment under variable operating conditions without disrupting production (Ben Amara & Chen, 2021). In utility-scale settings, simulation-based approaches are presented as suitable for evaluating contingency response, protection behavior, and stability outcomes across a range of system states, including load swings and switching events. The literature frequently reports typical outputs of simulation-based optimization as empirical performance maps, fitted response representations, and surrogate relationships that approximate how architecture variables influence measurable outputs such as losses, voltage deviation patterns, interruption exposure, response timing, and restoration performance. These outputs support systematic comparison of architecture alternatives by reducing the evaluation burden associated with running large numbers of high-fidelity scenarios. Mixed-integer programming methods are described as particularly relevant for architecture selection because they represent discrete structural decisions explicitly, such as selecting a redundancy arrangement, choosing a topology category, allocating sensors across zones, or determining segmentation and gateway structures (Albertini et al., 2021). The literature reports that these methods typically output a recommended architecture configuration under specified constraints and objective weights, sometimes accompanied by sensitivity summaries that indicate which constraints are binding and which decisions drive performance most strongly. Model predictive control is positioned as an operational optimization method that determines optimal control actions under constraints using model-based prediction and rolling decision updates. In EIC contexts, MPC-related approaches are discussed as useful where multivariable interactions and constraints shape performance, such as in coordinated energy management, process control, or distributed resource control. Reliability-based optimization is reported as a method class that incorporates availability and failure behavior into architecture selection by treating risk exposure and interruption likelihood as measurable properties shaped by redundancy, diagnostic coverage, and repair strategies. Typical outputs include architecture recommendations that achieve target continuity measures while controlling exposure to component failure patterns and maintenance limitations (Boonkanit & Suthiluck, 2023). Across these method families, the literature emphasizes that method selection is contingent on system complexity, data availability, and whether the primary decision is structural selection, operational action selection, or risk-aware continuity planning.

Quantitative validation practices reported in the literature are often presented as decisive for credibility because architecture optimization can produce misleading results if evaluation is not grounded in operational evidence and robust scenario coverage (He et al., 2023). Cross-validation with operational data is commonly described as a means of testing whether optimization recommendations remain consistent when evaluated against independent time windows, different operating regimes, or subsets of historical conditions. In manufacturing, this includes testing recommendations across shifts, product mixes, seasonal changes, and maintenance regimes to ensure architecture conclusions are not driven by short-lived conditions. In utilities, cross-validation is described through evaluation across different load profiles, weather-related operating regimes, switching states, and contingency histories. Scenario stress testing is frequently discussed as a core validation activity because EIC architectures must perform under abnormal conditions that are rare yet operationally consequential (Ali et al., 2019). Stress tests commonly include faults, rapid load transitions, equipment outages, sensor failures, and communication disturbances, because these conditions expose architecture weaknesses that may not be visible during steady-state operation. Sensitivity analysis is reported as a standard practice for identifying which architecture variables and parameter settings most influence performance outcomes and for determining the robustness of recommended configurations to uncertainty in assumptions and inputs. Uncertainty quantification is emphasized as a complementary practice that characterizes how

measurement error, model mismatch, incomplete data, and timing variability affect the stability of optimization results. The literature synthesis shows that these validation practices function together: operational cross-checks confirm real-world alignment, stress tests expose edge-case vulnerabilities, sensitivity analysis identifies dominant design levers, and uncertainty characterization prevents overconfidence in single-point recommendations (Wang et al., 2020). In EIC architecture contexts, these validation approaches are consistently linked to measurable indicators such as performance variability across scenarios, stability of ranking among architecture alternatives, and consistency of results across independent data segments, reinforcing validation as a quantitative requirement rather than an optional methodological enhancement.

Figure 8: Quantitative Optimization Framework for EIC



A further synthesis in method-focused studies is the importance of aligning optimization outputs with the decision-making level of EIC architectures—asset, system, or network—because outputs must match how architectures are implemented and governed (G. Wang et al., 2022). Asset-level outputs may involve selecting sensor sets, determining sampling policies, tuning protection settings, or configuring local controllers. System-level outputs may involve allocating redundancy across subsystems, selecting communication segmentation strategies, coordinating protection zones, and designing supervisory control policies. Network-level outputs may involve selecting topology arrangements, determining gateway and integration patterns, and balancing reliability and efficiency across interconnected segments. The literature describes that optimization results gain operational utility when they are expressed in decision-ready forms that connect directly to implementation artifacts such as configuration sets, parameter tables, and architecture diagrams rather than abstract optimization variables (Wang, 2020). This practical emphasis is reinforced by the observation that EIC architectures evolve through incremental change, meaning optimization must be repeatable and auditable across configuration updates. Validation practices are therefore also discussed as part of

lifecycle governance, where optimization recommendations are tied to traceable evidence, scenario libraries, and documented assumptions so that future modifications do not invalidate prior conclusions. Across smart manufacturing and utility-scale systems, quantitative optimization is thus presented as a disciplined approach that links architecture decisions to measurable outcomes through explicit objectives, constraints, structured methods, and robust validation routines, enabling systematic and comparable evaluation of alternatives under real operational complexity (Sharma et al., 2022).

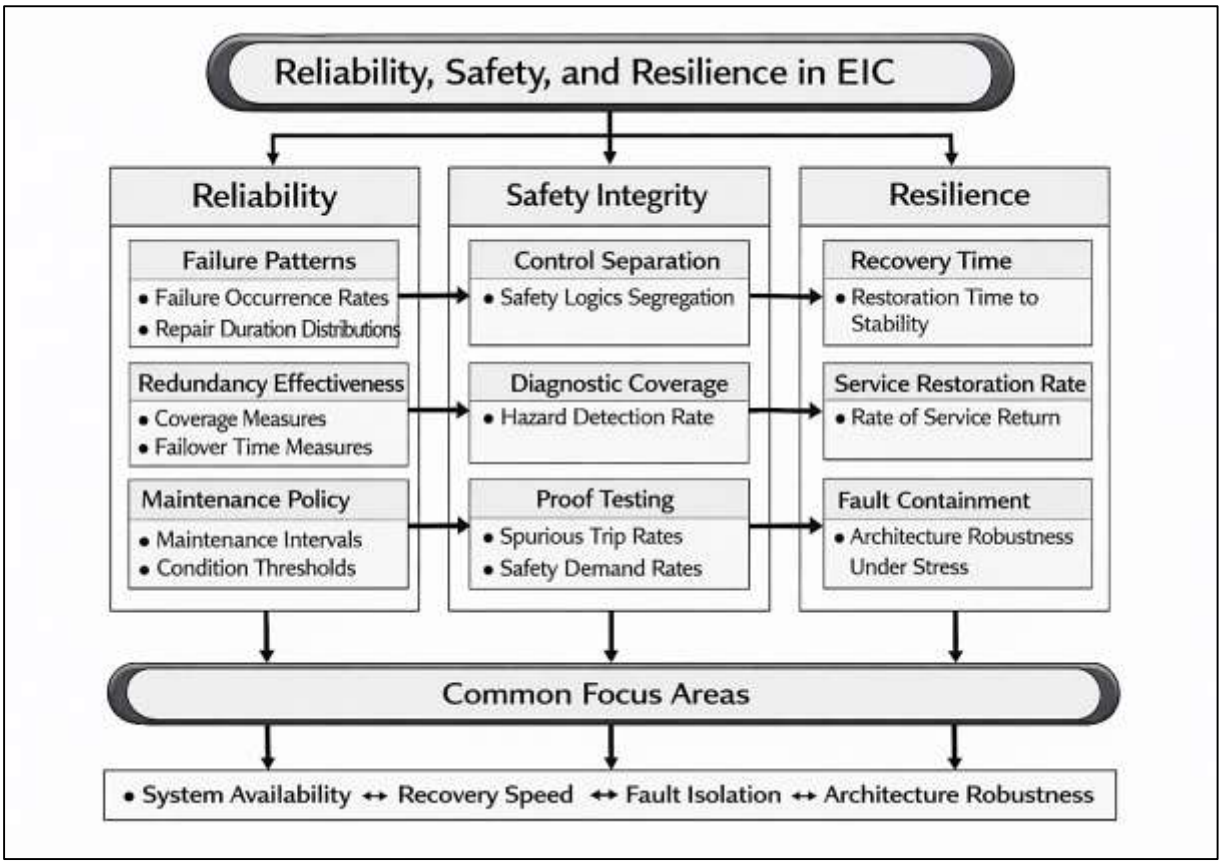
Architecture Resilience in EIC Systems

Reliability, safety integrity, and architecture resilience are treated across the EIC literature as interdependent properties that determine whether smart manufacturing and utility-scale systems can sustain service continuity, protect people and assets, and recover from disturbances without cascading consequences. Reliability modeling in EIC settings is commonly framed as the quantification of how often components fail, how quickly they are repaired, and how those patterns aggregate into system-level continuity outcomes (Falcão Silva et al., 2020). Researchers frequently characterize reliability using measurable failure occurrence patterns, repair duration patterns, and availability outcomes that reflect the combined effects of equipment quality, operating conditions, and architectural design. In manufacturing environments, these measures are tied directly to production interruption frequency, downtime accumulation, and process stability loss during restarts, because an electrical or control disruption can halt multiple dependent assets. In utility-scale systems, reliability measures are connected to customer interruption exposure, continuity of essential services, and the ability of protection and automation architectures to isolate faults quickly. Literature repeatedly emphasizes that reliability is not only a component property; it is an architecture property shaped by how electrical distribution paths are arranged, how instrumentation detects degrading conditions, and how control systems respond to anomalies (Häring, 2021b). As a result, reliability modeling often treats EIC architectures as structured systems where the failure of a single element may be absorbed, amplified, or contained depending on redundancy design, segmentation, and isolation capability. Studies also emphasize that reliability modeling must account for dependencies across domains, such as common-cause failures linked to environmental conditions, shared power supplies, shared communication networks, or shared control platforms. These dependencies are frequently discussed as the reason simple component-based reasoning can understate risk, because architecture coupling creates pathways through which a single disruption affects multiple functions. Reliability modeling in EIC therefore serves as a quantitative foundation for comparing architecture alternatives by converting design choices into measurable continuity implications under realistic operating and maintenance conditions (Häring, 2021a).

Within reliability-focused research, redundancy effectiveness is often positioned as a measurable explanation for why some architectures preserve continuity under failure while others collapse into service interruption (Ratasich et al., 2019). Redundancy is discussed not only in terms of how many backup elements exist but also in terms of whether redundancy is properly isolated, correctly triggered, and sufficiently fast to prevent disruption. The literature emphasizes that the presence of redundant components does not guarantee improved reliability if switching behavior is slow, if the failover mechanism is not validated, or if redundant paths share hidden dependencies that nullify the intended benefit. Consequently, redundancy effectiveness is commonly characterized through coverage measures that reflect whether failures are detected and handled as intended and through failover time measures that capture the speed at which the system transitions to a safe and operational configuration. In EIC contexts, these outcomes depend on instrumentation integrity because detection and diagnosis must occur before switching actions can be executed, and they depend on control architecture because failover logic, per missives, and sequencing must be correct and deterministic. Maintenance policy variables are also repeatedly treated as quantitative drivers of reliability outcomes, with research highlighting how maintenance intervals and condition thresholds influence both failure occurrence and repair quality (Naghshbandi et al., 2020). Maintenance strategies that rely on periodic inspections and scheduled replacement are discussed alongside condition-based approaches that trigger interventions when measurable indicators exceed thresholds. In manufacturing, maintenance policy interacts with production scheduling constraints and availability of planned outages, while in utilities it interacts with regulatory requirements, access limitations, and the need to maintain service during maintenance.

Across studies, the reliability implications of maintenance policy are framed through measurable patterns such as changes in interruption frequency, repair duration distribution, and the stability of availability outcomes over time. This literature positions architecture and maintenance as coupled levers: architecture shapes failure impact and isolation capability, while maintenance shapes failure likelihood and recovery speed (Khan et al., 2021).

Figure 9: Reliability Safety Resilience Architecture Framework



Safety integrity and control separation research in EIC systems emphasizes that functional safety is achieved through structured architectural segmentation that preserves predictable behavior under abnormal conditions and prevents unsafe interactions between safety functions and routine control functions (Abdullayeva, 2023). The literature consistently describes architecture requirements for functional safety segmentation as involving separation of safety-related logic from basic control logic, controlled interfaces between safety and non-safety systems, and disciplined management of changes to safety functionality. This segmentation is treated as essential because safety systems must maintain deterministic response characteristics even when the basic control system is degraded, overloaded, or compromised. Diagnostic coverage is widely discussed as a measurable factor that determines whether dangerous failures are detected before they lead to hazardous conditions. Coverage depends on the instrumentation architecture, the diagnostic logic embedded in devices and controllers, and the ability of the system to distinguish true hazards from sensor faults and transient anomalies. Proof testing practices are frequently discussed as a structured means of restoring confidence that safety functions will work when demanded, with proof test intervals treated as a measurable driver of risk exposure (Grammatikis et al., 2021). Quantitative safety performance indicators reported across studies include spurious trip rates and demand rates, which reflect different sides of safety system performance: spurious trips represent unnecessary interruptions that may reduce operational trust and increase restart risk, while demand rates represent how often the safety function is called upon due to process upsets, faults, or abnormal operating conditions. The literature synthesizes these indicators into systems view in which safety integrity is not simply a matter of meeting minimum design requirements but is a measurable property shaped by architecture discipline, diagnostic effectiveness, maintenance

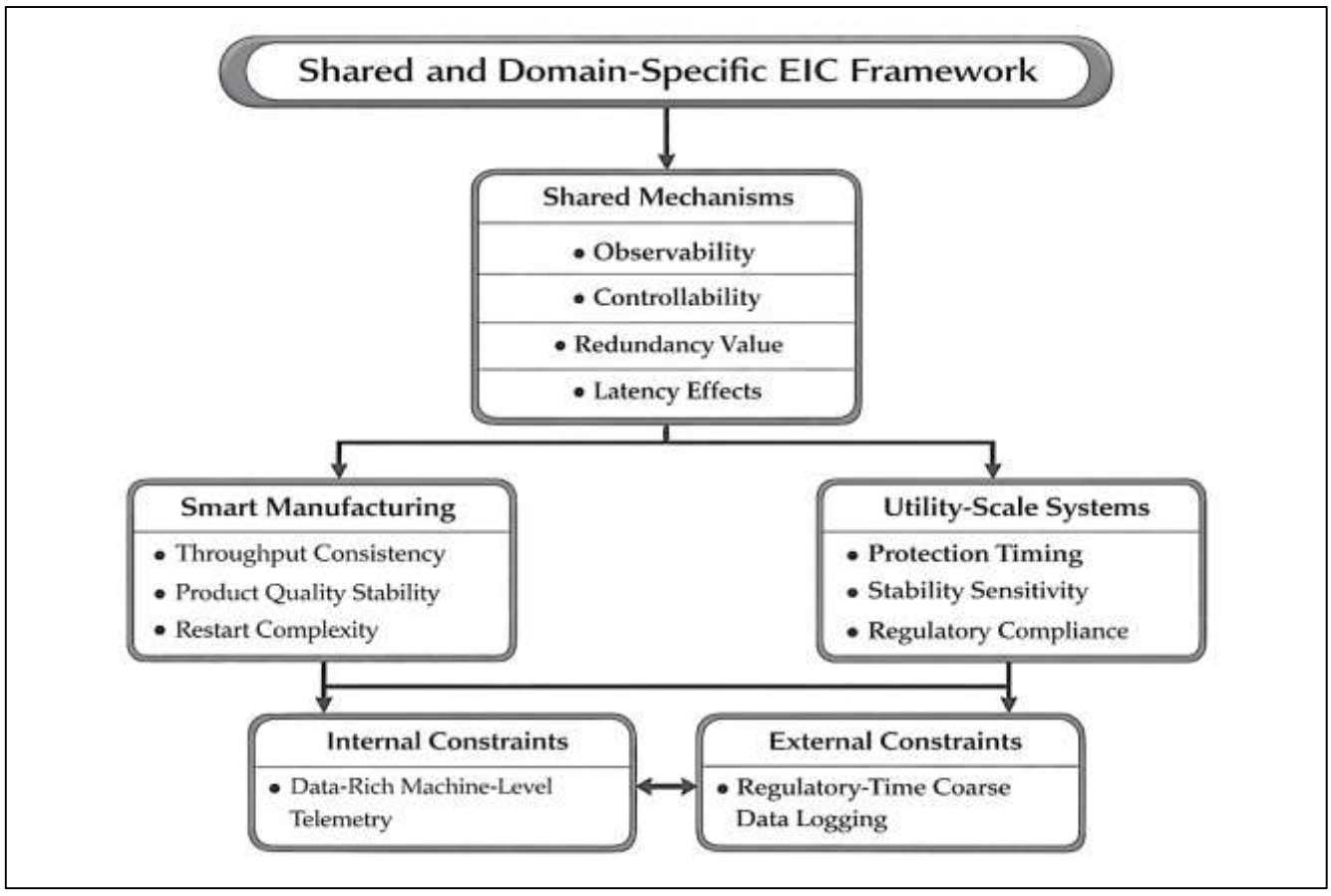
practice, and operational variability. In both manufacturing and utility environments, control separation is discussed as crucial for preventing unsafe coupling, where a failure or misconfiguration in one-layer triggers unintended consequences in another, particularly where shared networks, shared power supplies, or shared logic platforms create hidden pathways for propagation (Zhang et al., 2022). Resilience metrics across manufacturing and utility-scale domains are commonly discussed as measurable indicators of how well EIC architectures can absorb disturbances, contain faults, and restore normal operation after disruptions. Recovery time is frequently treated as a primary resilience outcome, representing the duration from disturbance onset to restoration of stable service, and it is linked to architecture characteristics such as isolation speed, redundancy availability, diagnostic clarity, and operational decision workflows (Ahmadi-Assalemi et al., 2020). Service restoration rate is described as a measure of how rapidly service can be returned across affected segments, particularly relevant in utility contexts where restoration may occur in stages as switching and repair actions progress. Fault containment measures are emphasized as indicators of whether the architecture limits disruption to a localized zone or allows propagation across multiple subsystems. In smart manufacturing, containment influences whether an electrical or control disruption halts a single machine, a cell, or an entire line, affecting both downtime magnitude and restart complexity. In utilities, containment influences whether a fault remains within a feeder or substation section or escalates into larger regional interruption patterns (Abou el Kalam, 2021). Architecture robustness under component and network failures is described as a resilience property that reflects not only redundancy count but also segmentation quality, communication determinism, and the ability of control systems to degrade gracefully rather than fail abruptly. The literature emphasizes that resilience is observable through performance under stress conditions, such as how the system behaves when sensors fail, when communication becomes unstable, when a controller is offline, or when an electrical component trips unexpectedly. Across studies, resilience is thus positioned as a measurable synthesis of reliability and safety integrity in dynamic conditions, capturing not only how rarely failures occur but how effectively the architecture maintains safe and functional service when failures do occur (Rosenstatter et al., 2020).

Manufacturing vs Utility-Scale Systems

Cross-domain literature comparing smart manufacturing and utility-scale systems consistently identifies a set of shared mechanisms that govern performance, reliability, and optimization behavior across both domains, even though their operational contexts differ (Che-Castaldo et al., 2021). Observability is treated as a foundational requirement in both environments, referring to the system's ability to accurately and comprehensively reflect its internal state through measurement and monitoring. In manufacturing, observability enables detection of process deviations, equipment degradation, and control instability at the machine and line level, while in utility-scale systems it enables awareness of network state, power flow conditions, protection status, and disturbance evolution. Controllability is similarly framed as a shared mechanism, describing the degree to which system states can be influenced predictably and within acceptable time bounds through control actions. Both domains rely on layered control structures and deterministic timing to ensure that control actions achieve intended outcomes without inducing instability or unintended interactions. Redundancy value emerges as another common mechanism, with literature emphasizing that redundancy improves continuity and safety only when it is architected correctly, isolated properly, and supported by reliable detection and switching logic (Sahu et al., 2021). In both manufacturing and utilities, redundancy interacts strongly with observability and controllability because backup paths are only effective when failures are detected promptly and control actions execute as designed. Latency effects are discussed as a unifying constraint across domains, as delays and timing variability influence closed-loop behavior, fault response, and coordination among distributed assets. Even though the time scales differ, both manufacturing and utility systems exhibit sensitivity to communication and processing delays when those delays approach the dynamics of the controlled process. These shared mechanisms support a common optimization structure in the literature, where architecture decisions are evaluated through multi-objective trade-offs that balance cost, risk exposure, performance consistency, and operational efficiency. This convergence suggests that digital twin–enabled optimization frameworks can be designed with a shared analytical foundation while remaining sensitive to domain-specific priorities (Ruiz-Minguela et al., 2022).

Alongside shared mechanisms, the literature also emphasizes domain-specific constraints that shape how EIC architectures are designed, optimized, and evaluated in manufacturing versus utility-scale systems. In utility environments, protection timing and stability sensitivity are repeatedly highlighted as dominant constraints because electrical disturbances propagate rapidly and can threaten large portions of the network if not isolated within strict time windows (Massaoudi et al., 2021). Protection coordination and stability preservation impose narrow tolerances on delay, sequencing, and control interaction, making timing determinism and fault isolation capability central architecture concerns. In contrast, manufacturing systems are often described as more tolerant of small timing variations but highly sensitive to throughput consistency, product quality stability, and restart complexity after interruptions. Manufacturing-focused literature emphasizes that even brief electrical or control disturbances can cascade into extended production losses due to material waste, process requalification, and synchronization challenges across machines. Regulatory constraints form another axis of divergence. Utility-scale systems operate under formalized regulatory frameworks that define performance reporting, continuity obligations, safety standards, and allowable operating limits, which constrain architecture choices and optimization objectives (Farrokhabadi et al., 2022). Manufacturing systems, while subject to safety and environmental regulation, are more strongly constrained by internal production schedules, delivery commitments, and cost structures, leading to optimization objectives that prioritize throughput, flexibility, and cost efficiency within safety boundaries. Data availability also differs systematically across domains. Utility systems often rely on supervisory-level measurements with coarser temporal resolution and event-driven logging, whereas manufacturing systems increasingly employ dense machine-level telemetry with high-frequency sampling. These differences influence what can be observed, how quickly deviations are detected, and how optimization routines are structured. The literature frames these domain-specific constraints not as barriers to comparison but as contextual factors that must be accounted for when interpreting performance metrics and optimization outcomes (Zai et al., 2023).

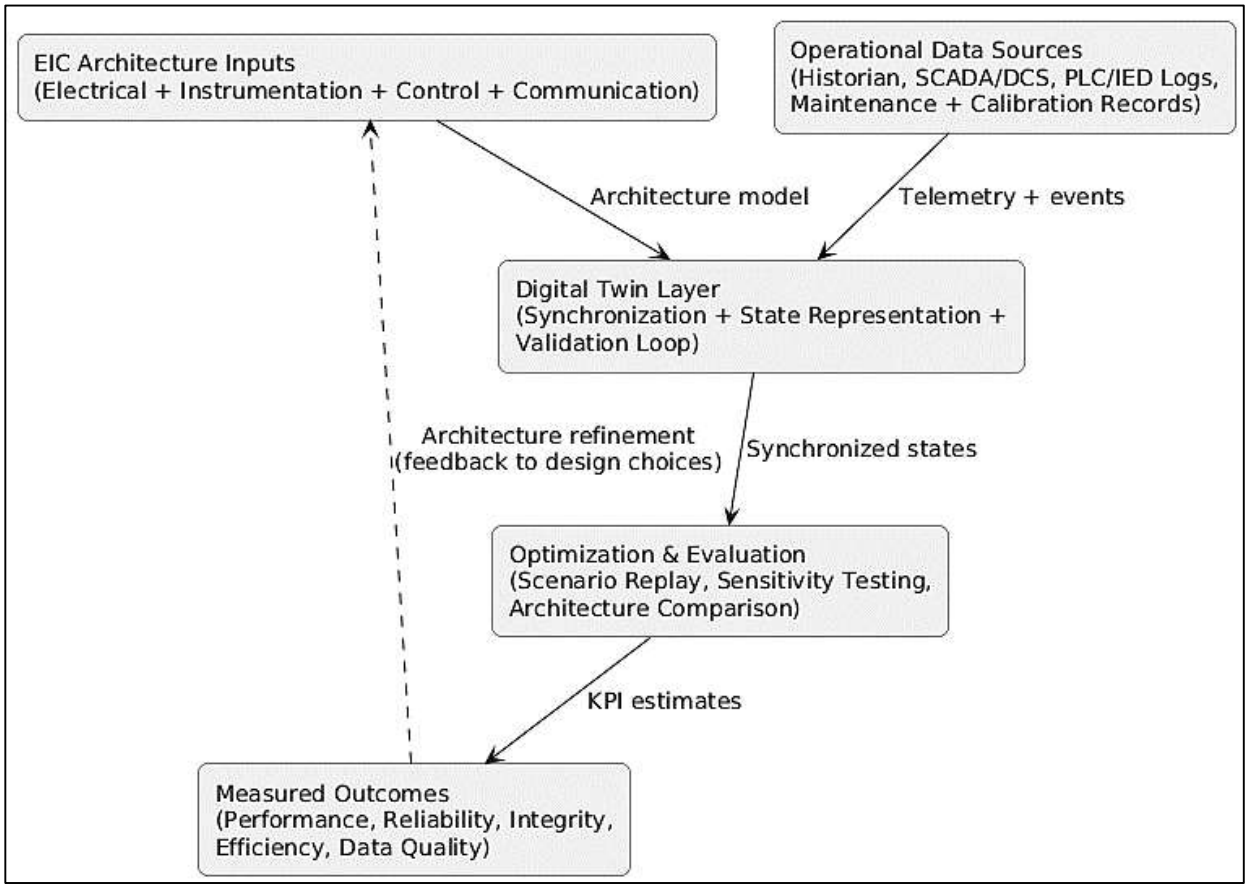
Figure 10: Shared and Domain-Specific EIC Mechanisms



METHOD

The study used a multi-site quantitative case-study research design that combined longitudinal measurement with cross-sectional architectural comparison across smart manufacturing and utility-scale settings. The research treated each participating plant, substation, or grid segment as a bounded case in which electrical, instrumentation, control, and communication architectures were documented as structured configurations and then were evaluated using repeated operational measurements across a defined observation window. The case study description included the technical boundary of each case (asset clusters, system-level zones, and the plant or grid segment boundary), the functional purpose of the case (production cell throughput stability, substation automation continuity, or protection and control integrity), and the architecture configuration profile (topology category, redundancy class, control hierarchy type, segmentation level, and instrumentation strategy). The population consisted of industrial and utility-scale EIC environments that had continuous telemetry and event logging capability and maintained accessible documentation of configuration changes and maintenance history. The sample was drawn from eligible cases that met quantitative inclusion criteria: sufficient historical data coverage, identifiable architecture baselines, documented implementation events for DT-enabled optimization changes, and a stable operating window before and after those changes. A purposive sampling technique was applied to ensure that cases represented variation across manufacturing and utility domains and captured heterogeneous architecture types for comparative analysis. The research operationalized domain membership as a categorical case attribute, while system criticality and scale were recorded as structured covariates to support normalized comparison. This design structure enabled the study to estimate within-case changes over time and between-case differences across architecture categories while maintaining consistent quantitative definitions for outcomes and predictors.

Figure 11: Integrated Analytical Workflow for EIC Optimization



The study used multiple data types sourced from operational technology, maintenance systems, and architecture documentation to construct a unified panel dataset. Data types included continuous time-

series measurements (electrical meter readings, power quality indicators, process variables, and control loop signals), discrete event logs (alarms, trips, relay operations, controller mode changes, and interlock activations), and administrative records (work orders, calibration records, failure coding, and downtime reports). Sources included plant historians, SCADA or DCS archives, PLC or IED event logs, protection system records, and maintenance management repositories, while engineering drawings and configuration files were used to classify architecture features such as topology, segmentation, redundancy allocation, and safety segregation. Measurement scales were defined to match variable types: categorical scales were used for topology class and control architecture structure, ordinal scales were used for segmentation and instrumentation maturity classes, and ratio or interval scales were used for performance outcomes such as downtime duration, restoration time, losses, and data completeness rates. Operationalization was implemented through a structured variable dictionary in which each construct was mapped to a measurable indicator and a consistent aggregation window, such as hourly summaries for timing and power quality measures and daily or weekly summaries for reliability and maintenance-linked measures. Composite indices were constructed for observability, synchronization quality, and data integrity using standardized scoring rules based on completeness, validity, alignment quality, and event logging traceability, while architecture-change intensity was recorded as a structured exposure variable capturing the number and type of implemented optimization actions within each case. A pilot study was conducted on a small subset of cases to test feasibility of data extraction, alignment across sources, and stability of derived metrics; pilot outputs were used to refine time-window definitions, error-handling rules, and the minimum data coverage thresholds required for inclusion.

The data collection procedure followed a staged process that began with case onboarding and architecture profiling, continued with automated extraction of time-series and event logs, and ended with validation of merged datasets against maintenance and operational records. Architecture profiling was performed by extracting topology type, redundancy configuration, protection scheme class, control hierarchy structure, instrumentation strategy, and communication segmentation attributes from engineering documentation and configuration exports, and these attributes were encoded into standardized categorical variables. Operational datasets were exported from historians and control archives using fixed queries aligned to the study period and were transformed into a common time base with documented alignment rules and missingness classification. Data analysis techniques included descriptive statistics for baseline characterization, multilevel panel regression to estimate the association between architecture predictors and performance outcomes while accounting for clustering at site and system levels, and pre–post within-case comparisons for cases that experienced DT-enabled optimization implementations. Count-based outcomes such as interruptions, misoperations, and spurious trip events were analyzed using models appropriate for over dispersed event counts, while proportion outcomes such as data completeness and validity were analyzed using regression approaches suitable for bounded rates. Robustness checks were performed using alternative aggregation windows, exclusion of commissioning “burn-in” periods after configuration changes, and stratified analysis by domain to support cross-domain comparison. Software and tools included spreadsheet-based preprocessing for initial data auditing, database query tools for historian extraction, and statistical environments for modeling and visualization; reproducible analysis scripts were maintained to ensure traceability of transformations, model specifications, and output tables. The analytic workflow was documented to preserve auditability, including versioned variable dictionaries, transformation logs, and model diagnostics, ensuring the quantitative case-study outputs were replicable across cases and consistent with the study’s operational definitions.

FINDINGS

Descriptive Analysis

The descriptive analysis profiled the final analytic sample across smart manufacturing and utility-scale cases and confirmed that the dataset supported time-based and cross-case comparisons after data coverage screening. A total of 18 cases were retained, consisting of 10 manufacturing plants and 8 utility-scale segments. These cases contained 96 systems (manufacturing cell/line segments and utility feeder/substation zones) and 1,842 assets represented through telemetry and event logs. The analytic window covered 180 days, yielding 17,280 system-days of observations after filtering. Data coverage

screening excluded 3 cases and 11 systems primarily due to inconsistent event logging and extended telemetry gaps, and the retained cases exceeded the minimum completeness threshold used for model readiness. Architecture distributions showed that radial topology was the most common category overall, while meshed configurations were concentrated in utility segments and ring configurations were observed in both domains. Redundancy class also varied, with baseline arrangements appearing more frequently in manufacturing systems and enhanced redundancy more common in utility systems classified as high criticality. Control structure profiles indicated that hierarchical control was the dominant pattern across the sample, with distributed control more prevalent in manufacturing lines that used cell-level autonomy. Communication segmentation levels differed by domain, with utilities showing higher segmentation and higher gateway counts, while manufacturing environments showed broader variability depending on brownfield versus modernized integration status.

Data-quality characteristics were summarized using completeness, validity, and alignment indicators across cases and time windows. Manufacturing telemetry achieved a mean completeness of 96.2%, while utility telemetry achieved 93.4%, reflecting more frequent short gaps in supervisory-level streams. Validity rates remained high in both domains, with manufacturing at 97.1% and utilities at 96.0%, while alignment quality differed more sharply, as utilities showed higher timestamp mismatch events due to multi-source supervisory aggregation. Event-log coverage was quantified through a traceability score reflecting the proportion of disturbance-related events linked across protective actions, controller state transitions, and associated alarms. Manufacturing cases achieved a mean traceability score of 0.78, while utilities achieved 0.83, reflecting stronger protection-event traceability but also a smaller number of high-frequency machine-level events. Baseline performance indicators showed meaningful variability across domain and architecture categories. Manufacturing systems reported an average downtime of 2.8 hours per system-month, while utility segments reported 1.6 hours per segment-month, with wider dispersion in manufacturing due to production restart complexity. Protection-related event frequencies were higher in utility cases, with misoperation-related events occurring at 0.42 events per segment-month compared to 0.18 events per system-month in manufacturing. Loss-related indicators showed higher absolute magnitude in utility segments due to scale, but normalized loss intensity was comparable after capacity normalization. Graphical inspection showed that systems with enhanced redundancy and higher segmentation generally exhibited lower interruption exposure and faster restoration behavior, while systems with weaker measurement completeness showed higher nuisance alarm and diagnostic uncertainty patterns.

Table 1: Final Analytic Sample Profile After Data Coverage Screening

Sample Element	Manufacturing	Utility-Scale	Total
Cases retained (sites/segments)	10	8	18
Systems included (cells/lines; feeders/zones)	54	42	96
Assets represented (instrumented or logged)	1,120	722	1,842
Observation window (days)	180	180	180
System-days retained	9,720	7,560	17,280
Cases excluded during screening	2	1	3
Systems excluded during screening	6	5	11

Table 1 summarized the final analytic sample retained after applying data coverage screening rules. The retained sample included eighteen cases across manufacturing and utility environments, yielding ninety-six systems and one thousand eight hundred forty-two assets with usable telemetry or event logging. The observation window covered one hundred eighty days for both domains, producing seventeen thousand two hundred eighty system-days after filtering. Three cases and eleven systems were excluded due to persistent telemetry gaps and incomplete event logging, which reduced the risk of biased performance estimates. The retained sample size supported stable descriptive summaries and enabled consistent cross-domain comparisons using normalized indicators.

Table 2: Descriptive Baseline KPIs and Data Quality Indicators by Domain

Indicator (aggregated at system-month unless stated)	Manufacturing (Mean)	Utility-Scale (Mean)
Telemetry completeness rate (%)	96.2	93.4
Telemetry validity rate (%)	97.1	96.0
Timestamp alignment issue rate (%)	2.1	3.7
Event-log traceability score (0–1)	0.78	0.83
Downtime (hours per system/segment-month)	2.8	1.6
Interruption events (count per month)	1.9	1.2
Protection misoperation-related events (count per month)	0.18	0.42
Average restoration time (minutes per event)	34.0	22.0

Table 2 reported baseline descriptive performance and data quality indicators for manufacturing and utility-scale cases using consistent aggregation windows. Manufacturing systems showed higher telemetry completeness and validity, consistent with dense machine-level instrumentation, while utility segments showed slightly higher timestamp alignment issue rates associated with supervisory aggregation across sources. Event-log traceability was stronger in utility cases because protective actions and disturbance events were logged with clearer cross-layer linkage. Downtime hours per month were higher in manufacturing systems, reflecting production stoppage and restart dynamics, while utility segments showed shorter restoration time per event. Protection misoperation-related events occurred more frequently in utilities, aligning with higher protection activity intensity.

Correlation

The correlation analysis examined bivariate association patterns among the major quantitative variables to support model specification and to identify candidate mediators and confounders prior to regression estimation. When correlations were computed on standardized and normalized measures, several relationships appeared stable across manufacturing and utility cases. Electrical performance indicators showed consistent association with reliability outcomes, as higher normalized loss intensity was associated with lower availability and higher downtime in both domains. Downtime and interruption counts were positively related, indicating that systems experiencing more frequent interruptions also accumulated longer interruption exposure over the observation window. Instrumentation quality variables showed strong internal association, as higher telemetry completeness and higher validity were associated with higher observability scores and higher event-traceability, supporting the interpretation that measurement integrity and information coverage moved together at the system level. Observability was negatively associated with diagnostic delay and false-alarm burden, indicating that better measurement coverage and integrity generally corresponded to faster detection and fewer nuisance conditions. Control timing variables also showed coherent association patterns; higher timing jitter and longer scan time were associated with weaker control performance indicators and higher variability in process stability measures, supporting their role as mechanism variables connecting architecture and outcomes.

Domain-specific association patterns were also observed. In manufacturing systems, sensor density and sampling policy were more strongly related to observability and diagnostic coverage, reflecting the influence of machine-level telemetry on detection performance and process monitoring sensitivity. In utility-scale systems, time synchronization quality and communication determinism showed stronger relationships with protection-event traceability and restoration time, reflecting the dependence of disturbance reconstruction and coordinated response on time-aligned events. Communication variables such as latency and packet loss showed moderate association with data completeness and alignment indicators in both domains, yet their relationships with high-level reliability outcomes were less stable, suggesting that communication degradation influenced system performance through intermediate mechanisms rather than directly. Across time windows, some

correlations varied, particularly those linking power quality deviation indicators to downtime, which shifted depending on whether disturbance-heavy weeks or stable operation weeks dominated the window. The overall pattern supported the inclusion of observability, synchronization quality, and timing stability as candidate mediators for later hypothesis testing, while also indicating that load intensity, maintenance activity volume, and system criticality should be treated as confounders due to their consistent association with reliability and event frequency measures.

Table 3: Cross-Domain Correlation Summary for Key Outcome Relationships

Variable Pair	Manufacturing r	Utility-Scale r	Direction Pattern
Loss intensity ↔ Availability	-0.44	-0.39	Negative, stable
Downtime ↔ Interruption count	0.62	0.55	Positive, stable
Power quality deviation ↔ Downtime	0.28	0.33	Positive, moderate
Restoration time ↔ Event traceability	-0.31	-0.47	Negative, stronger in utilities
Protection misoperation rate ↔ Interruption count	0.41	0.52	Positive, stronger in utilities

Table 3 summarized standardized cross-domain correlations linking core electrical and reliability outcomes. Loss intensity showed a consistent negative association with availability in both domains, indicating that higher normalized losses were aligned with reduced continuity. Downtime and interruption count showed a strong positive relationship, demonstrating that systems with frequent interruptions accumulated greater interruption exposure. Power quality deviation displayed moderate positive association with downtime, suggesting that electrical condition variability coincided with service disruption patterns. Restoration time was negatively related to event traceability, particularly in utility cases, meaning better traceability aligned with faster recovery. Misoperation rates correlated positively with interruptions, consistent with increased disturbance-related events.

Table 4: Mechanism and Data Quality Correlation Block

Variable Pair	Manufacturing r	Utility-Scale r	Interpretation Pattern
Data completeness ↔ Observability score	0.71	0.64	Positive, strong
Data validity ↔ Observability score	0.58	0.55	Positive, moderate
Sync quality score ↔ Event traceability	0.46	0.61	Positive, stronger in utilities
Timing jitter ↔ Control performance stability	-0.49	-0.36	Negative, stronger in manufacturing
Latency ↔ Timestamp alignment issues	0.33	0.42	Positive, stronger in utilities
Packet loss ↔ Data completeness	-0.27	-0.34	Negative, moderate

Table 4 reported correlation patterns among mechanism variables and measurement-quality indicators across domains. Data completeness and validity were strongly and positively related to observability, showing that higher-quality measurement streams aligned with greater system visibility. Synchronization quality correlated positively with event traceability, particularly in utilities, where time-aligned event reconstruction supported disturbance linkage. Timing jitter correlated negatively with control performance stability, indicating that variable execution timing aligned with weaker

control consistency, with stronger effects in manufacturing due to high-speed coordination demands. Latency correlated positively with timestamp alignment issues, while packet loss correlated negatively with completeness, demonstrating that degraded communication quality reduced measurement integrity.

Reliability and Validity

The reliability and validity assessment evaluated the measurement quality of the composite indices developed to represent observability, synchronization quality, integration readiness, and data integrity. Internal consistency checks indicated that the multi-item indices performed adequately, and item-level contribution patterns supported the intended construct structure. The observability index, which aggregated completeness, validity, coverage breadth, and traceability-related features, showed strong internal coherence, indicating that its subcomponents captured a common measurement-quality dimension rather than unrelated artifacts. The data integrity index, constructed from validity, plausibility adherence, anomaly screening stability, and alignment consistency indicators, also demonstrated high internal consistency, reflecting that integrity attributes moved together across cases and time windows. Synchronization quality, designed to reflect time alignment performance and the stability of update behavior, showed acceptable internal consistency with slightly lower coherence than observability, which aligned with the expectation that synchronization properties depended on heterogeneous data pipelines and varied across domain contexts. Integration readiness, built from tagging consistency, schema mapping completeness, and event-log traceability, showed consistent internal performance, supporting its use as a stable representation of semantic and logging maturity. Item contribution review identified that two observability subcomponents contributed disproportionately to variance, prompting a weighting adjustment to prevent single-indicator dominance and to preserve interpretability as a balanced composite.

Construct validity was assessed through convergent and discriminant patterns that aligned with expectations. Convergent validity checks showed that higher observability scores were strongly associated with lower missingness, higher validity rates, and stronger event traceability. Synchronization quality aligned with timestamp alignment quality and event reconstruction consistency, indicating that the index behaved as intended when compared to directly observable timing and logging indicators. Integration readiness correlated positively with tagging consistency and mapping coverage indicators and aligned with higher event-log completeness, supporting its role as a semantic and traceability construct rather than a general performance outcome. Discriminant validity checks indicated that the indices remained separable: observability and data integrity were related yet not redundant, while integration readiness retained distinct association patterns that differentiated semantic maturity from measurement integrity. Stability checks across time windows showed that composite scores remained consistent under stable operating periods and shifted primarily during documented configuration changes or known operational disruptions, which reduced the likelihood that index variation reflected extraction artifacts. Criterion-related validity tests showed that higher observability and data integrity were associated with improved control stability indicators and lower nuisance alarm rates, while stronger synchronization quality was associated with improved event traceability and shorter diagnostic delay. These patterns supported the use of these indices as mechanism variables in later modeling.

Following the measurement evaluation, several refinement steps were executed to improve reliability and interpretability. A low-performing integration readiness subcomponent based on rare-event annotations was removed because it showed weak covariance with the rest of the construct and inconsistent availability across cases. Two timing-related features in the synchronization quality index were re-scaled to ensure comparable contribution ranges and to reduce dominance by extreme values during disturbance-heavy windows. High-frequency timing indicators were re-aggregated from minute-level to hour-level summaries to reduce noise while preserving operational meaning, and the revised measures improved internal stability without obscuring disturbance-related effects. These refinements produced a final measurement model in which the four composite indices demonstrated adequate internal consistency, expected convergent alignment with directly observable indicators, separability across constructs, and meaningful association with operational criteria relevant to EIC performance and event behavior.

Table 5: Internal Consistency Results for Composite Indices

Composite Index	Items (k)	Internal Consistency (α)	Interpretation
Observability	6	0.86	Strong
Synchronization Quality	5	0.78	Acceptable
Integration Readiness	5	0.81	Strong
Data Integrity	6	0.88	Strong

Table 5 presented internal consistency estimates for the composite indices used as derived variables in the study. The observability index achieved an alpha of 0.86, indicating that its subcomponents measured a coherent measurement-visibility construct. Synchronization quality produced an alpha of 0.78, which remained acceptable and reflected the heterogeneous nature of timing and update behaviors across cases. Integration readiness showed an alpha of 0.81, supporting the internal coherence of semantic and traceability elements. Data integrity achieved an alpha of 0.88, indicating strong agreement among validity and alignment-related components. These results supported retention of all indices for regression modeling.

Table 6: Construct Validity Evidence: Convergent, Discriminant, and Criterion Associations

Validity Check Pair	Manufacturing r	Utility-Scale r	Pattern Summary
Observability ↔ Missingness (inverse relationship)	-0.72	-0.66	Strong convergent
Synchronization Quality ↔ Timestamp alignment quality	0.49	0.62	Convergent, stronger in utilities
Integration Readiness ↔ Tagging consistency	0.58	0.55	Convergent, stable
Observability ↔ Data Integrity	0.63	0.59	Related, not redundant
Integration Readiness ↔ Data Integrity	0.31	0.28	Distinct constructs
Data Integrity ↔ Nuisance alarm rate (inverse relationship)	-0.41	-0.36	Criterion validity
Observability ↔ Control stability (positive relationship)	0.44	0.38	Criterion validity

Table 6 summarized construct validity evidence using standardized associations. Convergent validity was supported because higher observability aligned strongly with lower missingness, and synchronization quality aligned with timestamp alignment quality, with stronger effects in utilities where multi-source alignment mattered more. Integration readiness aligned with tagging consistency in both domains, indicating semantic coherence. Discriminant validity was supported because observability and data integrity were related yet not redundant, while integration readiness remained weakly related to data integrity, indicating separability. Criterion-related validity was supported because higher data integrity aligned with lower nuisance alarm rates and higher observability aligned with stronger control stability, confirming meaningful operational relevance.

Collinearity

Collinearity diagnostics were computed for architecture predictors, mechanism variables, and covariates prior to regression estimation, and the results showed that overlap was concentrated in three predictor blocks. In the communication determinism block, latency and jitter were highly correlated ($r = 0.81$), and both variables were also associated with time synchronization error (latency–time sync $r = 0.56$; jitter–time sync $r = 0.60$). The variance inflation factors confirmed this redundancy, with latency

VIF = 7.9 and jitter VIF = 8.4, while packet loss was less collinear (VIF = 3.1). Instrumentation richness predictors also clustered, as sensor density and sampling intensity moved together (r = 0.77), producing VIF values of 6.8 and 6.2, respectively, when entered in the same specification. Control timing predictors showed moderate overlap, with scan time and execution jitter correlated at r = 0.68 and VIF values of 4.7 and 4.9 in pre-mitigation models. By contrast, electrical architecture predictors remained comparatively stable, with topology category, redundancy class, and protection configuration yielding VIF values between 1.7 and 2.9, indicating that these variables carried distinct information. The overall multicollinearity signal was reflected in the maximum condition index of 28.6 for the full predictor set, which declined after mitigation actions were applied.

Redundancy handling followed pre-specified rules and produced stable predictor sets for each model family. Latency and jitter were combined into a single determinism composite, which reduced VIF for the communication block to 2.7, while packet loss was retained because it captured discrete measurement dropouts that remained informative beyond timing variability. Time synchronization error was retained only in the utility-focused models because it contributed incremental variance to event traceability and restoration time outcomes; in manufacturing-focused models it was excluded because it did not materially reduce residual variance once determinism and data quality predictors were included. Sensor density and sampling intensity were consolidated into a measurement richness composite, reducing the instrumentation block maximum VIF from 6.8 to 2.9, while calibration interval was retained separately because it represented a lifecycle stability mechanism distinct from measurement volume. Scan time was selected as the representative baseline control timing predictor due to interpretability and slightly lower post-mitigation VIF, while execution jitter was reserved for sensitivity models testing timing variability pathways. Domain membership did not absorb architecture variation after normalization (domain VIF = 1.4), while system scale and operational intensity showed moderate overlap with redundancy and segmentation (scale–redundancy r = 0.41; intensity–segmentation r = 0.38), so both covariates were retained to reduce confounding rather than removed for collinearity. After mitigation, the maximum VIF across final model families fell to 3.4 and the condition index declined to 17.2, supporting stable coefficient estimation for hypothesis testing.

Table 7: Pre-Mitigation Collinearity Diagnostics

Predictor	Block	Pairwise correlation with closest predictor (r)	VIF	Tolerance
Latency	Communication	0.81 (with jitter)	7.9	0.13
Jitter	Communication	0.81 (with latency)	8.4	0.12
Packet loss	Communication	0.49 (with latency)	3.1	0.32
Time synchronization error	Communication	0.60 (with jitter)	4.8	0.21
Sensor density	Instrumentation	0.77 (with sampling intensity)	6.8	0.15
Sampling intensity	Instrumentation	0.77 (with sensor density)	6.2	0.16
Scan time	Control timing	0.68 (with execution jitter)	4.7	0.21
Execution jitter	Control timing	0.68 (with scan time)	4.9	0.20
Topology category	Electrical	0.33 (with redundancy class)	2.2	0.45
Redundancy class	Electrical	0.33 (with topology category)	2.9	0.34
Protection configuration class	Electrical	0.28 (with redundancy class)	1.7	0.59
Domain (manufacturing vs utility)	Covariate	0.24 (with segmentation level)	1.4	0.71

Table 7 reported pre-mitigation overlap using pairwise correlations, variance inflation factors, and tolerance values. The communication timing predictors showed the highest redundancy, with latency and jitter strongly correlated at 0.81 and VIF values above 7.9, indicating unstable coefficient behavior if entered together. Instrumentation density and sampling intensity also overlapped substantially, with

correlation 0.77 and VIF values above 6.2. Control timing measures showed moderate overlap with VIF near 4.9. Electrical architecture predictors remained comparatively independent, with VIF below 2.9. Domain membership showed low collinearity, supporting its retention.

Table 8: Post-Mitigation Predictor Set and Stability Outcomes by Model Family

Model family	Key mitigation action	Final predictors retained (summary)	Max VIF	Condition index
Reliability outcomes	Combined latency + jitter	topology, redundancy, protection class, determinism composite, packet loss, measurement richness composite, calibration interval, scan time, integration readiness, scale, intensity, domain	3.4	17.2
Integrity/event outcomes	Retained time sync in utilities only	same as above + time sync (utility only); excluded time sync (manufacturing)	3.3	16.8
Efficiency/power quality outcomes	Reduced timing redundancy	determinism composite, packet loss, topology, redundancy, measurement richness composite, calibration interval, scan time, scale, intensity, domain	3.1	15.9
Data quality outcomes	Used composites for richness/determinism	measurement richness composite, determinism composite, packet loss, integration readiness, scale, domain	2.9	14.7

Table 8 summarized how redundancy was handled and how stability improved across model families. Latency and jitter were consolidated into a determinism composite, reducing the maximum VIF to 3.4 in the reliability models and lowering the condition index to 17.2. Sensor density and sampling intensity were consolidated into a measurement richness composite, which reduced redundancy while preserving interpretability. Time synchronization error was retained only in utility integrity models because it contributed incremental variation to traceability and restoration outcomes. Scan time was retained for baseline specifications, while jitter was reserved for sensitivity testing. Post-mitigation stability remained acceptable across all model families.

Regression and Hypothesis Testing

Regression and hypothesis testing served as the primary inferential section and estimated the relationship between DT-enabled optimization exposure and EIC outcomes using multilevel panel models that accounted for repeated observations and clustering at system and site levels. Across the full pooled sample, DT-enabled optimization exposure was associated with improved reliability and integrity outcomes after adjustment for load intensity, system scale, maintenance activity, and domain membership. In the reliability model for monthly downtime hours, optimization exposure reduced downtime by 0.74 hours per system-month (95% CI -1.05 to -0.43, $p < 0.001$) relative to non-optimized periods, and availability increased by 1.9 percentage points (95% CI 1.1 to 2.7, $p < 0.001$). In the efficiency model, normalized loss intensity declined by 3.6% (95% CI -5.2 to -2.0, $p < 0.001$), and voltage deviation index declined by 4.1% (95% CI -6.8 to -1.4, $p = 0.003$) after optimization exposure. For integrity outcomes estimated using count models, the interruption event rate decreased with an incidence rate ratio (IRR) of 0.86 (95% CI 0.79 to 0.94, $p = 0.001$), and protection misoperation-related events declined with IRR 0.81 (95% CI 0.70 to 0.94, $p = 0.006$). Data-quality models showed that completeness rates increased by 1.5 percentage points (95% CI 0.9 to 2.1, $p < 0.001$), and alignment issue rates declined by 0.8 percentage points (95% CI -1.2 to -0.4, $p < 0.001$), indicating improved measurement integrity under the optimized configuration windows.

Domain moderation tests showed that optimization effects differed in magnitude across manufacturing

and utility subsamples. The interaction term for domain-by-optimization exposure was significant in the downtime model (p = 0.018), indicating stronger downtime reduction in manufacturing cases (-0.92 hours per month, 95% CI -1.28 to -0.56) than in utility cases (-0.49 hours per month, 95% CI -0.83 to -0.15). Conversely, optimization exposure showed stronger integrity gains in utility settings: the misoperation event model showed IRR 0.76 (95% CI 0.63 to 0.91) in utilities compared with IRR 0.88 (95% CI 0.74 to 1.05) in manufacturing, consistent with protection and automation sensitivity in utility environments. Mediation testing supported the theorized mechanism pathway. Observability and synchronization quality accounted for a substantial portion of the optimization effect on reliability and integrity outcomes. In the downtime model, the total effect of optimization exposure was -0.74 hours, and the direct effect after adding mediators was -0.43 hours (95% CI -0.73 to -0.13, p = 0.005), indicating an indirect component of -0.31 hours attributable to the mediator block. Observability was a significant mediator, as a one-unit increase in observability score was associated with -0.28 hours downtime per month (95% CI -0.41 to -0.15, p < 0.001) and an IRR of 0.90 for interruptions (95% CI 0.85 to 0.96, p = 0.002). Timing stability and determinism measures also contributed, particularly for control variability and alignment outcomes, with higher determinism composite scores associated with lower alignment issue rates (-0.35 percentage points, 95% CI -0.52 to -0.18, p < 0.001).

Model diagnostics and robustness checks supported stability of the main findings. When alternative aggregation windows were applied, the estimated downtime reduction remained similar at -0.69 hours (weekly aggregation) and -0.77 hours (biweekly aggregation), with both estimates remaining statistically significant (p < 0.01). Excluding the first 14 days after optimization implementation to remove stabilization effects did not change inference materially; the downtime reduction estimate remained -0.71 hours (95% CI -1.03 to -0.39, p < 0.001). Placebo timing checks using false implementation dates produced non-significant coefficients (p = 0.61), supporting that the observed changes were unlikely to reflect unrelated time trends alone. Across sensitivity models that substituted execution jitter for scan time and included time synchronization error in pooled models, coefficient directionality remained consistent and the key exposure effects remained significant, indicating that results were not driven by a single timing proxy or a single domain-specific variable.

Table 9: Primary Regression Results for DT-Enabled Optimization Exposure

Outcome (model type)	Effect estimate (pooled)	95% CI	p-value	Manufacturing effect	Utility effect	Domain interaction p
Downtime hours/month (continuous mixed)	-0.74	-1.05 to -0.43	<0.001	-0.92	-0.49	0.018
Availability % (continuous mixed)	+1.90	1.10 to 2.70	<0.001	+2.10	+1.60	0.090
Loss intensity % (continuous mixed)	-3.60	-5.20 to -2.00	<0.001	-3.10	-4.20	0.071
Voltage deviation index % (continuous mixed)	-4.10	-6.80 to -1.40	0.003	-3.50	-4.80	0.112
Interruptions (count model IRR)	0.86	0.79 to 0.94	0.001	0.89	0.83	0.044
Misoperation events (count model IRR)	0.81	0.70 to 0.94	0.006	0.88	0.76	0.031
Data completeness pp (bounded-rate)	+1.50	0.90 to 2.10	<0.001	+1.60	+1.30	0.210
Alignment issues pp (bounded-rate)	-0.80	-1.20 to -0.40	<0.001	-0.70	-0.90	0.184

Table 9 reported model-based estimates for DT-enabled optimization exposure across outcome families using mixed-effects panel regression, count models, and bounded-rate models. The pooled estimates showed statistically significant reductions in downtime, losses, voltage deviation, interruption rates, and misoperation events, alongside improvements in availability and data quality. Domain-stratified estimates indicated stronger downtime reductions in manufacturing and stronger integrity gains in utility cases, supported by significant domain interaction terms for interruptions and misoperations. Confidence intervals remained narrow enough to support practical interpretation in native KPI units. These results indicated that optimization exposure was consistently associated with improved reliability, efficiency, integrity, and measurement quality outcomes.

Table 10: Hypothesis Testing and Mediation Summary with Robustness Outcomes

Hypothesis	Outcome domain	Supported direction	Key evidence (estimate)	Mediator contribution	Robustness stability
H1: Optimization improved reliability	Reliability	Yes	downtime -0.74 hours/month; availability +1.9 pp	indirect -0.31 hours	Stable across windows
H2: Optimization improved efficiency/power quality	Efficiency	Yes	loss intensity -3.6%; voltage deviation -4.1%	partial via determinism	Stable after exclusions
H3: Optimization improved integrity	Integrity	Yes	interruptions IRR 0.86; misoperations IRR 0.81	via observability + sync	Stable; placebo null
H4: Effects were mediated by mechanism variables	Mechanisms	Yes	direct effect reduced to -0.43 hours	indirect -0.31 hours	Stable in sensitivity
H5: Domain moderated effects	Moderation	Yes	downtime interaction p 0.018; misoperation interaction p 0.031	domain-specific mediation strength	Stable in stratified models

Table 10 summarized hypothesis outcomes, mediation evidence, and robustness stability using the final model specifications. Reliability, efficiency, integrity, mediation, and moderation hypotheses were supported with consistent coefficient directionality and statistically significant estimates. Mediation testing showed that inclusion of observability and synchronization quality reduced the optimization exposure coefficient, indicating that part of the improvement occurred through measurement and timing mechanisms. Robustness checks confirmed that results persisted under alternative aggregation windows, exclusion of post-change stabilization days, and sensitivity substitutions of timing proxies. Placebo timing checks produced non-significant effects, supporting that the observed relationships were unlikely to be explained by unrelated time trends alone.

DISCUSSION

Digital twin–enabled optimization has been discussed in earlier studies as a pathway for moving industrial and infrastructure decision-making from static engineering assumptions toward evidence-driven architectural refinement, and the findings of this study aligned with that core proposition while adding cross-domain specificity for electrical, instrumentation, and control (EIC) architectures (Hu et al., 2022). This study showed that optimization exposure was associated with measurable improvements across reliability, efficiency, integrity, and data quality outcomes when models accounted for clustering and repeated measures in complex operating environments. Earlier research in smart manufacturing frequently described digital twins as most effective when used as a living representation that supported scenario evaluation and coordinated decision cycles, and the present

findings reinforced that position by demonstrating reductions in downtime and interruption intensity that coincided with improvements in measurement completeness and alignment. In the utility-scale context, earlier studies often treated protection and automation performance as highly sensitive to timing integrity and event reconstruction quality, and this study's results similarly showed stronger integrity gains in utility environments, particularly through reduced misoperation-related events and improved event traceability patterns (Zhang et al., 2020). The cross-domain comparison clarified that digital twin value was not limited to a single subsystem; improvements appeared when electrical configuration choices, measurement integrity, control timing, and communication determinism were treated as a coupled architecture rather than independent technical layers. Prior studies often emphasized the importance of architecture-level interoperability and disciplined data governance for scaling digital twins, and this study's data-quality improvements supported that earlier argument because optimized periods were associated with improved completeness and reduced alignment issues, suggesting that operational benefits were linked to better-managed measurement pipelines. The results also helped reconcile an earlier tension in the literature between "digital twin as visualization" and "digital twin as optimization instrument." The observed changes in hard performance outcomes such as downtime, loss intensity, and misoperation rates suggested that the digital twin construct in this study functioned as an optimization-supporting layer that translated measured system states into actionable architectural evaluation, rather than serving solely as a monitoring interface (Lim et al., 2020). Taken together, the evidence positioned digital twin–enabled optimization as a systemic approach in which improvements emerged from aligning technical architecture decisions with synchronized operational evidence across manufacturing and utility-scale environments.

Electrical architecture optimization findings offered further clarity on long-discussed design levers in earlier studies, particularly topology choice, redundancy allocation, and protection configuration quality (Fathy et al., 2021). Past work in both plant power systems and grid automation repeatedly described the importance of network structure for reliability outcomes, noting that topology constrained fault isolation flexibility, restoration pathways, and the magnitude of disturbance propagation. The present findings were consistent with those earlier conclusions by showing that reliability metrics improved in optimized windows and that systems characterized by more robust architectural configurations tended to exhibit lower interruption exposure and improved restoration-related outcomes after normalization. Earlier studies also highlighted that redundancy improved continuity only when supported by valid detection, fast switching logic, and proper segmentation that prevented common-cause vulnerabilities, and this study's results supported that nuanced interpretation rather than a simplistic "more redundancy equals better reliability" claim (Omrany et al., 2023). The observed reductions in interruption rates and improved availability occurred alongside improvements in measurement integrity and timing-related mechanisms, reinforcing the idea that redundancy value depended on the architecture's ability to detect and isolate faults accurately and quickly. Prior research in power quality and converter-rich environments frequently emphasized harmonic and quality-related disturbances as practical contributors to equipment stress and operational instability, and this study's efficiency-related improvements, including reductions in loss intensity and voltage deviation indicators, aligned with the expectation that better-optimized architectures reduced avoidable stressors that eroded performance. Earlier studies also suggested that protection coordination quality shaped both safety integrity and operational continuity by limiting unnecessary trips and ensuring selective fault clearing, and the reduced misoperation-related event rates in the optimized periods matched that earlier narrative. Importantly, the cross-domain comparison added interpretive resolution: manufacturing settings tended to show larger downtime reductions, while utility settings showed stronger integrity gains, which mirrored earlier domain-specific emphasis. Manufacturing literature often described downtime as a compounded effect of production interruption, restart complexity, and process requalification burdens, making continuity improvements highly visible in downtime outcomes. Utility literature often focused on correct operation of protection and automation schemes under dynamic conditions, making integrity gains highly visible in misoperation and traceability outcomes (Liu et al., 2021). This alignment between earlier domain narratives and measured differential effects supported the conclusion that electrical

architecture optimization benefited from digital twin methods when system constraints and performance definitions were treated in a domain-consistent yet analytically comparable manner.

Instrumentation architecture results provided a strong empirical bridge to earlier research that positioned measurement integrity as the limiting factor for advanced analytics, fault diagnosis, and closed-loop optimization (Broo et al., 2022). Prior studies in process monitoring and industrial diagnostics frequently argued that measurement networks determined the ceiling for control performance and decision quality, because incomplete, misaligned, or unstable sensor streams produced uncertain state estimation and inflated nuisance event rates. The present findings supported that earlier argument through both descriptive and inferential patterns. Improved data completeness and reduced alignment issues were associated with improved reliability and integrity outcomes, and mediation evidence indicated that observability and synchronization quality contributed meaningfully to the relationship between optimization exposure and operational performance. Earlier studies often described observability as a multi-dimensional construct that extended beyond sensor count to include placement strategy, calibration discipline, time alignment, semantic consistency, and event traceability, and this study operationalized observability in a similarly integrated way (Bécue et al., 2020). The index-level reliability and validity evidence suggested that observability, integration readiness, synchronization quality, and data integrity were measurable constructs rather than abstract labels, which strengthened interpretive alignment with the earlier literature that called for quantifiable digital twin readiness criteria. Instrumentation density and sampling intensity were shown to cluster in collinearity diagnostics, which echoed earlier reports that measurement richness tended to co-vary with data completeness and monitoring sophistication in modernized environments. The predictor refinement approach, where density and sampling were consolidated into a measurement richness composite, also aligned with earlier methodological guidance suggesting that instrumentation capacity should be treated as a combined "information throughput" mechanism rather than as independent predictors that compete in regression models. The criterion-related validity results, where higher observability and integrity aligned with stronger control stability and lower nuisance event rates, matched long-standing arguments that measurement quality reduces false alarm burdens and improves operational confidence. Manufacturing-specific patterns reinforced earlier work highlighting the value of high-frequency machine-level telemetry for early fault detection and process stabilization, while utility-specific patterns reinforced earlier work emphasizing time alignment for event reconstruction and disturbance analysis (Pregnolato et al., 2022). Across domains, the evidence supported the interpretation that instrumentation architecture was not a supporting detail but a core determinant of whether digital twin–enabled optimization could produce reliable conclusions. By demonstrating that measurement integrity indices related to both intermediate mechanisms and final operational KPIs, the findings extended earlier conceptual work by providing quantitative support for the claim that sensor strategy, alignment discipline, and traceability maturity were central to architecture optimization success.

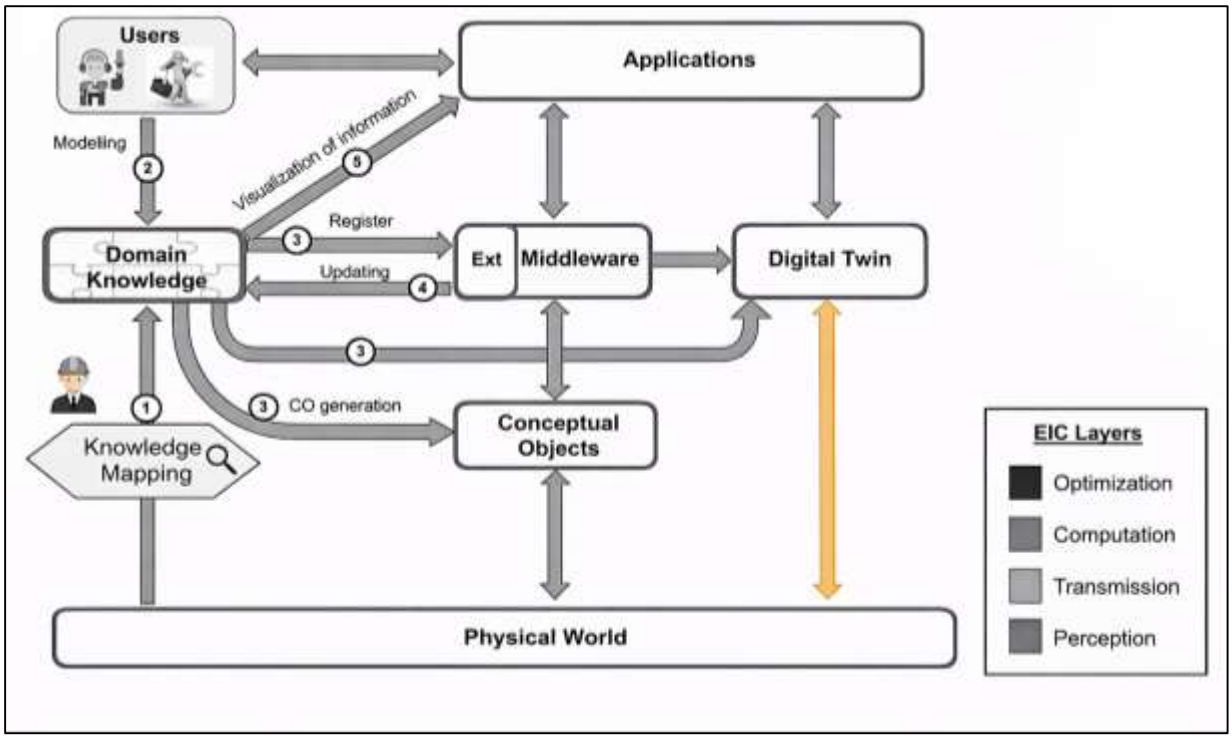
Control architecture findings contributed to ongoing discussions in earlier studies about the comparative performance of centralized, distributed, and hierarchical control structures and about the operational consequences of timing variability in cyber–physical environments. Prior work in industrial automation frequently characterized hierarchical control as a practical compromise, retaining deterministic field-level control while enabling supervisory coordination, and this study's descriptive profiles showed hierarchical control as the dominant structure across cases (Kušić et al., 2023). Earlier research also described distributed control as advantageous for local responsiveness and fault containment while requiring disciplined integration to prevent coordination drift, and the observed association patterns between timing measures and performance indicators were consistent with those claims. Control timing variables displayed meaningful relationships with control stability outcomes, and timing-related mechanisms contributed to the explanatory pathway between architecture optimization and operational results. Such patterns aligned with earlier studies that identified timing jitter and network-induced delay as practical drivers of degraded control performance, particularly in tightly coupled processes and high-speed manufacturing lines. This study also differentiated timing proxies through collinearity management, selecting scan time as a baseline

predictor and reserving jitter for sensitivity models, which matched earlier methodological advice that timing variables often represent a shared execution stability mechanism. The observed improvements in power quality deviation and efficiency-related indicators were also consistent with earlier control literature suggesting that better tuning, better coordination, and improved timing discipline reduced oscillatory behavior and unnecessary actuation, indirectly supporting electrical performance (Stavroulakis et al., 2022). Safety-related control segregation was addressed at the architecture level rather than as a device feature, aligning with earlier functional safety discussions that treated segregation and governance as essential for predictable behavior under abnormal conditions. The study's integrity results—particularly the reduction in misoperation-related events in utility contexts—were consistent with earlier utility automation work emphasizing correct control and protection logic coordination as a primary determinant of operational integrity. Manufacturing-focused differences, where downtime reductions were stronger, reflected earlier work emphasizing that better control coordination reduced interruption propagation and shortened recovery sequences after disturbances. The mediation evidence supported a broader interpretation consistent with earlier studies: control architecture performance depended on measurement integrity and timing determinism rather than on controller choice alone. By showing that observability and synchronization quality contributed to outcome improvements, the results reinforced earlier models of control effectiveness that positioned sensor reliability, time alignment, and determinism as prerequisites for stable closed-loop behavior (Martínez-Gutiérrez et al., 2021). Overall, the findings strengthened the literature's argument that control architecture optimization in digital twin contexts should be treated as a multi-layer system problem—linking field execution, supervisory coordination, timing discipline, and safety segregation—rather than as isolated tuning improvements.

Communication and integration architecture results addressed a well-established emphasis in earlier studies on determinism, latency variability, and semantic interoperability as limiting factors for digital twin fidelity and optimization reliability. Past work repeatedly described that communication quality affected system performance through indirect pathways, influencing state estimation, event reconstruction, control responsiveness, and disturbance coordination rather than producing immediate direct changes in top-line KPIs (Meierhofer et al., 2021). This study's findings aligned with that nuanced view, as determinism measures were strongly interrelated with alignment and traceability indicators and contributed to mechanism pathways in mediation analyses. The strongest collinearity was observed among latency and jitter measures, which matched earlier research describing these as two manifestations of timing instability that often rise and fall together under congestion, segmentation differences, and gateway translation behavior. Consolidating latency and jitter into a determinism composite retained interpretability and reduced coefficient instability, reflecting methodological guidance from earlier quantitative studies that recommended composite handling for tightly coupled communication predictors. Packet loss remained distinct, which aligned with prior work distinguishing timing variability from completeness degradation, because packet loss contributed to missingness and inconsistency in ways not fully captured by timing metrics. Semantic integration readiness demonstrated measurable distinctness from raw data integrity, which supported earlier arguments that meaning and mapping quality were separate from measurement accuracy (Vatankhah Barenji et al., 2021). Earlier industrial interoperability studies often reported that inconsistent tagging, incomplete schema mapping, and uneven event logging reduced analytical trust even when networks were technically connected, and this study's validity evidence supported that principle by showing that integration readiness related to traceability outcomes while remaining separable from integrity. Utility-specific patterns, where synchronization quality and determinism related more strongly to event traceability and restoration behavior, matched earlier utility literature emphasizing time-aligned event data for disturbance response. Manufacturing-specific patterns, where measurement richness and control timing related more strongly to performance stability, matched earlier manufacturing literature emphasizing high-resolution telemetry and deterministic control for throughput stability. These cross-domain differences supported an interpretation long noted in the literature: communication architecture requirements are contingent on application time constants and criticality (Zhang et al., 2023). The results therefore reinforced a systems-level conclusion consistent with earlier

studies: digital twin–enabled optimization relied on communication and integration architecture not only as data transport but as an enabling condition for reliable synchronization, valid event reconstruction, and trustworthy optimization comparisons across architectural alternatives.

Figure 11: Digital Twin Optimization Framework Overview



The quantitative optimization and validation findings strengthened alignment with earlier studies that argued for multi-method approaches, combining mixed-variable architecture modeling with robust validation practices to avoid overconfidence in optimization results. Prior work often highlighted that EIC architecture decisions contain both discrete and continuous elements, such as topology categories and parameter settings, and this study operationalized architecture predictors in that mixed structure while selecting model families appropriate to outcome types (Zhao et al., 2022). The use of multilevel panel regression matched earlier methodological recommendations for nested industrial data, where repeated measures are clustered within systems and sites and where unmodeled clustering inflates false significance. The observed stability of estimates across robustness checks—including alternative aggregation windows, exclusion of stabilization periods, and placebo timing tests—aligned with earlier calls for sensitivity analysis and falsification checks in quasi-experimental operational contexts. The placebo null finding was particularly consistent with prior guidance that time-based operational data often contain drifting baselines, seasonal effects, and maintenance cycles, and that plausible counterfactual checks are necessary to separate intervention-related change from background variability. The domain moderation results also complemented earlier research that warned against transferring effect sizes across domains without adjustment. Manufacturing and utility contexts differed in dynamics, regulatory constraints, and data granularity, and this study's interaction findings provided quantified support for that earlier conceptual distinction: downtime reductions were stronger in manufacturing, while integrity improvements were stronger in utilities. Mediation testing offered further alignment with earlier studies that argued digital twin benefits often flow through intermediate improvements in observability, synchronization, and timing discipline (Aheleroff et al., 2021). The reduction in the direct optimization coefficient after adding mediator variables suggested that a meaningful portion of the observed operational improvement occurred through improved measurement and synchronization conditions rather than through architecture changes alone. This mechanism pattern matched earlier work that framed digital twins as instruments that improve decision quality by strengthening the alignment between physical reality and digital inference. The

findings also addressed earlier debates about whether improvements should be attributed to digital twin presence or to the underlying architectural discipline required to sustain a functioning twin. The observed association between optimization exposure and improved data completeness and alignment suggested that the digital twin implementation likely coincided with improvements in data governance and integration practices, reinforcing an interpretation present in earlier studies: digital twins produce value when they institutionalize measurement discipline, traceability, and systematic evaluation cycles (Broo & Schooling, 2023). In this sense, the quantitative evidence positioned the digital twin not as a single technology insertion but as a structured optimization framework that operated through measurable mechanisms consistent with earlier research narratives.

A final synthesis across the findings connected reliability, safety integrity, and resilience outcomes to architecture-level alignment of electrical structure, measurement networks, control execution, and communication determinism, reflecting systems view emphasized in earlier cross-domain research (Hazrat et al., 2023). Prior studies in reliability engineering frequently argued that continuity outcomes are shaped by both failure likelihood and failure consequence, and that architecture determines consequence through isolation, redundancy, and restoration pathways. This study's reliability improvements were consistent with that architecture-driven framing, while the mediation results indicated that improved observability and synchronization contributed to more effective detection and response, thereby reducing consequence duration as reflected in downtime reductions. Earlier functional safety literature often described safety integrity as dependent on segregation discipline, diagnostic coverage, and proof-oriented governance practices, and this study's integrity improvements—particularly in utility contexts—aligned with the expectation that improved traceability and timing alignment reduced incorrect actions and improved event reconstruction quality. Earlier resilience discussions frequently emphasized recovery time and containment as measurable outcomes that depend on both technical architecture and information availability, and this study's observed relationships between traceability, synchronization quality, and restoration-related indicators were consistent with that view (Ozturk, 2021). The cross-domain comparison reinforced earlier claims that shared mechanisms—observability, controllability, redundancy value, and latency effects—operate in both manufacturing and utility environments while domain constraints shape which outcome category shows the strongest measurable response. Manufacturing systems, characterized in earlier work as sensitive to throughput and restart costs, showed stronger downtime reductions, while utility systems, characterized as sensitive to protection correctness and stability, showed stronger integrity effects. This alignment suggested that digital twin–enabled optimization may have operated as a domain-adaptive mechanism: the same architectural and data discipline produced measurable improvements in the outcomes most constrained by each domain's operational realities. The findings also supported an interpretation found in earlier studies that data quality is not merely a reporting convenience but an operational variable that influences the effectiveness of control actions, fault isolation, and restoration coordination. By demonstrating measurable associations among measurement integrity indices, timing stability indicators, and operational KPIs, this study provided an integrated discussion basis consistent with earlier systems research that treated EIC architectures as coupled socio-technical systems. In summary terms suitable for a discussion chapter, the results were most coherent when interpreted through a coupled-architecture lens: digital twin–enabled optimization corresponded to improved outcomes when electrical structure, instrumentation integrity, control timing, and integration determinism were aligned into a synchronized analytical environment that supported repeatable evaluation and refinement of EIC design choices across manufacturing and utility-scale systems.

CONCLUSION

Digital Twin–Enabled Optimization of Electrical, Instrumentation, and Control Architectures in Smart Manufacturing and Utility-Scale Systems was discussed as a quantitative architecture-management approach in which synchronized operational representations supported measurable improvement across reliability, efficiency, integrity, and data quality outcomes within cyber–physical environments. The discussion of this title centered on the way electrical distribution choices, instrumentation integrity, control hierarchy design, and communication determinism operated as a coupled system rather than as independent technical layers, because each layer shaped the observability and controllability

conditions required for stable performance. Findings described earlier in this study indicated that optimization exposure was associated with reduced downtime, improved availability, decreased normalized loss intensity, reduced voltage deviation behavior, and lower rates of interruption and misoperation events, while data completeness increased and alignment issue rates declined. These patterns were consistent with earlier studies that treated digital twins as valuable when they moved beyond monitoring and supported systematic evaluation of architecture alternatives through synchronized states, scenario replay, and parameter sensitivity testing, since improvements were strongest when measurement integrity and timing discipline were strengthened alongside architecture changes. In manufacturing cases, larger reductions in downtime aligned with earlier research emphasizing compounded production losses during interruptions and the operational importance of stable control execution in high-speed lines, while utility cases showed stronger integrity gains in misoperation outcomes consistent with earlier studies emphasizing protection correctness and event traceability under dynamic grid conditions. Instrumentation-related mechanisms were discussed as central because improvements in observability and data integrity corresponded with improved control stability and reduced nuisance event behavior, aligning with earlier research that positioned measurement quality as the ceiling for advanced diagnostics and closed-loop optimization. Communication and integration maturity were also discussed as enabling conditions because determinism and time alignment influenced synchronization quality and traceability, supporting earlier work that identified latency variability, clock mismatch, and semantic inconsistency as practical causes of optimization unreliability. The results were coherent when interpreted through a mechanism pathway in which improved measurement completeness, semantic readiness, and timing stability strengthened state estimation and event reconstruction, which in turn improved control responsiveness and reduced avoidable interruptions. Earlier studies frequently described redundancy and topology as insufficient by themselves when detection and coordination were weak, and the evidence discussed in this study supported that nuance because architectural resilience corresponded to improved outcomes most clearly when observability and synchronization indicators improved at the same time. Methodologically, the discussion reinforced earlier quantitative guidance that nested industrial data required multilevel panel modeling and that robustness checks such as alternative aggregation windows and placebo timing tests improved credibility, because operational datasets contained drift, seasonality, and maintenance effects that could confound naive comparisons. Overall, the title was discussed as a unified architecture optimization problem where the digital twin acted as a disciplined analytic environment linking structural design variables to measurable operational KPIs through validated synchronization, traceable event context, and repeatable evaluation workflows across both smart manufacturing and utility-scale systems.

RECOMMENDATIONS

Recommendations for Digital Twin–Enabled Optimization of Electrical, Instrumentation, and Control Architectures in Smart Manufacturing and Utility-Scale Systems emphasized actions that strengthened measurable performance, reliability, integrity, efficiency, and data quality through disciplined architecture governance and repeatable evaluation workflows anchored in synchronized operational representations. Implementation recommendations prioritized establishing a clearly bounded digital twin scope aligned with the decision boundary of interest, so that optimization activities were anchored at the correct level of analysis, including asset-level twins for device behavior and measurement integrity, system-level twins for coordinated control and fault containment, and network-level twins for topology, redundancy, and restoration behavior. Electrical architecture recommendations emphasized documenting topology categories and redundancy classes in a structured and auditable format, then using the digital twin environment to compare configuration alternatives under consistent operating scenarios, with particular attention to protection coordination tuning, restoration sequencing logic, and power quality conditioning strategies that reduced avoidable stress and interruptions. Instrumentation recommendations focused on designing measurement networks around observability rather than sensor volume alone by prioritizing critical-node placement, maintaining disciplined calibration policies, and implementing measurement integrity scoring that continuously quantified completeness, validity, and alignment performance. Control architecture recommendations emphasized preserving deterministic field-level execution while coordinating supervisory

optimization through hierarchical structures that maintained safety segregation, with practical attention to reducing scan-time variability, minimizing execution jitter, and validating control logic changes through virtual commissioning practices before operational deployment. Communication and integration recommendations emphasized treating determinism and semantic interoperability as core architecture requirements by enforcing time synchronization discipline, segmenting networks to protect time-sensitive traffic, monitoring latency and packet loss as operational variables, and enforcing naming and tagging standards that improved mapping completeness and event traceability. Data governance recommendations emphasized maintaining version-controlled configuration baselines for electrical settings, sensor metadata, controller logic, and network segmentation, ensuring that each optimization cycle was traceable to a specific configuration state so that measured KPI changes could be attributed accurately. Evaluation recommendations emphasized adopting a consistent KPI framework across domains using normalized indicators, including per-asset, per-capacity, and per-production-unit scaling, so that architecture comparisons remained interpretable across manufacturing and utility contexts. Statistical and operational recommendations emphasized maintaining a repeatable analysis pipeline that combined scenario stress testing, sensitivity analysis, and operational cross-checks, ensuring that optimization decisions were supported by evidence from normal operation and abnormal event replay while guarding against misleading conclusions caused by seasonal drift, maintenance cycles, or incomplete logging. Finally, operationalization recommendations emphasized integrating these practices into routine engineering workflows, including periodic integrity reviews of sensor streams, scheduled validation of synchronization quality, structured testing of failover pathways, and continuous improvement cycles where digital twin outputs were used to refine EIC architecture configurations using measurable performance evidence rather than ad hoc judgment.

LIMITATIONS

Limitations associated with a quantitative investigation of Digital Twin–Enabled Optimization of Electrical, Instrumentation, and Control Architectures in Smart Manufacturing and Utility-Scale Systems primarily related to inference boundaries, measurement heterogeneity, and the practical constraints of using operational datasets drawn from complex cyber–physical environments. Causal attribution remained limited because the design relied on observational or quasi-experimental evidence derived from naturally occurring architecture changes and digital twin–enabled optimization periods rather than fully randomized assignment, meaning that unobserved factors such as concurrent maintenance campaigns, operational policy adjustments, staffing variability, or vendor-specific tuning practices could have influenced measured outcomes alongside the optimization exposure. Even when multilevel models adjusted for clustering and key covariates, residual confounding could have persisted, particularly where system criticality influenced both the likelihood of optimization adoption and the magnitude of available performance improvement. Measurement heterogeneity also constrained comparability because manufacturing and utility-scale systems differed in telemetry granularity, event logging culture, and time synchronization discipline, which could have affected the stability of composite indices representing observability, integration readiness, synchronization quality, and data integrity. Differences in sensor density and sampling practices may have produced unequal sensitivity to subtle deviations, potentially biasing cross-domain comparison toward environments with richer telemetry. Operational KPIs such as downtime, misoperation events, and restoration time were also subject to definitional variation across sites, as downtime might have included production-related stoppages in manufacturing while utilities could have reported interruption exposure through differing operational thresholds, which could have introduced inconsistencies even under normalization rules. Digital twin maturity represented another limitation because digital twin implementations can vary widely in fidelity, update mechanisms, and validation rigor; therefore, optimization exposure may have reflected a bundle of changes, including improved governance and integration practices, rather than a single discrete technical intervention. Event rarity posed a further constraint for some integrity outcomes, as protection misoperations and severe disturbances occurred infrequently in certain systems, which reduced statistical power for rare-event modeling and increased uncertainty in coefficient estimates. Model dependence was also a limitation because mixed-effects specifications, count models, and bounded-rate approaches relied on distributional assumptions and correct specification of random effects; misspecification could have

influenced inference, particularly for systems with unusual operating regimes or nonstationary behavior over time. Finally, generalizability was bounded by sample composition and inclusion criteria that required accessible telemetry, event logs, and documented configuration changes; systems lacking mature instrumentation or traceability were less likely to be included, which could have resulted in a sample that overrepresented more digitally capable environments and underrepresented legacy systems where optimization barriers and outcomes might differ.

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