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PLC–SCADA–Integrated Electrical Automation Frameworks for Process Optimization in Water and Wastewater Treatment Facilities

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Abstract

This quantitative study examined the operational impact of PLC–SCADA–integrated electrical automation frameworks on process optimization in water and wastewater treatment facilities using high-frequency operational data and quasi-experimental evaluation methods. A longitudinal interrupted time series design was applied to 720 daily observations, equally divided between pre-integration and post-integration periods, with statistical adjustment for influent flow, temperature, operating regime, and major equipment availability. The findings showed consistent and statistically significant improvements across efficiency, stability, workload, and event-based performance indicators. Energy intensity exhibited an immediate post-integration level reduction of 0.041 kWh/m³ (95% CI −0.056 to −0.026, $p < .001$) and an additional post-integration trend improvement of 0.00018 kWh/m³ per day ($p = .002$), indicating both immediate and sustained efficiency gains. Process stability improved through a reduction in composite stability deviation of 0.043 units ($p < .001$) and a 22% decrease in excursion event rates (IRR = 0.78, 95% CI 0.70–0.87). Supervisory workload outcomes improved markedly, with alarm rates declining by 28.4 alarms per day ($p < .001$), alarm flood events reduced to 73% of baseline frequency (IRR = 0.73, $p < .001$), and manual override time reduced by 1.6 percentage points ($p < .001$). Chemical intensity showed a statistically significant immediate reduction of 2.6 mg/L ($p = .001$) but no significant post-integration trend change. Mechanism-oriented analyses indicated a 9.2% reduction in VFD speed variability and a 0.36-unit reduction in loop oscillation proxy scores ($p < .001$), supporting a control-stability pathway for observed outcomes. Sensitivity analyses using storm-only periods, influent-matched windows, and outage-excluded datasets produced consistent effect directions and comparable magnitudes. Overall, the results demonstrated that PLC–SCADA–electrical integration was associated with measurable and robust improvements in energy efficiency, process stability, abnormal-event frequency, and operator workload under real treatment-plant operating variability.

Keywords

PLC–SCADA integration; Electrical automation; Process optimization; Water treatment; Wastewater facilities.

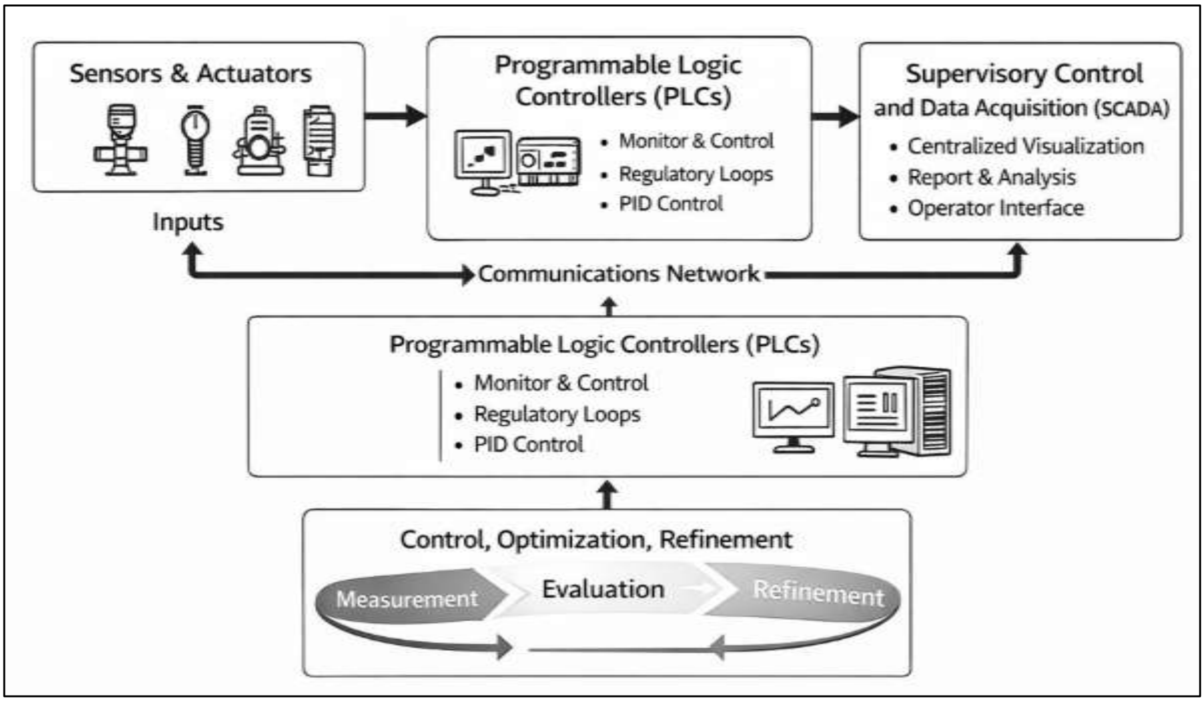
INTRODUCTION

Programmable logic controllers (PLCs) are industrial digital controllers designed to execute deterministic logic in real time by repeatedly scanning inputs, running a control program, and updating outputs (Sehr et al., 2020). Supervisory control and data acquisition (SCADA) systems are supervisory platforms that collect operational data from distributed assets, visualize process conditions through human–machine interfaces, manage alarms and events, archive time-series histories, and support supervisory setpoint and command functions. In water and wastewater treatment facilities, a PLC–SCADA–integrated electrical automation framework refers to the coordinated engineering of instrumentation, power and motor control, control logic, communications networks, and supervisory applications so that unit processes can be monitored, controlled, and verified with high reliability. The framework is not limited to a technical pairing of a controller and a monitoring screen; it defines how sensors, actuators, electrical drives, protective devices, control sequences, and supervisory workflows collectively regulate treatment performance. International significance arises from the universal dependence on safe drinking water, effective wastewater management, and environmental protection, alongside the reality that treatment plants operate continuously under variable influent conditions and tight compliance limits (Mellado & Núñez, 2022). These facilities serve as critical infrastructure in both developed and developing contexts, influencing public health outcomes, industrial productivity, ecosystem quality, and urban resilience. As utilities expand capacity and modernize aging assets, automation frameworks become foundational to measurable operational stability because they define the repeatability of control actions and the integrity of operational evidence captured through plant data. In quantitative terms, integrated automation determines whether key indicators—energy intensity, chemical consumption rates, compliance variability, alarm burdens, equipment availability, and process stability—can be measured consistently and improved systematically (Serhane et al., 2019). This makes PLC–SCADA integration a central engineering pathway for process optimization, where optimization is understood as improving measurable performance under safety, quality, and operational constraints.

Process optimization in water and wastewater treatment can be defined as the systematic improvement of operational outcomes, expressed through quantified objectives such as reducing energy use, minimizing chemical dosing, stabilizing effluent quality, decreasing downtime, and lowering variability in critical process variables (Tasca et al., 2020). Optimization is not a single action but a structured cycle of measurement, control, evaluation, and refinement, where the facility's physical processes are dynamic and disturbance-driven. Influent flow, pollutant loads, temperature, and hydraulic shocks vary across hours and seasons, creating a nonstationary operating environment. Within this context, integrated PLC–SCADA frameworks enable closed-loop and supervisory control structures that respond consistently to disturbances while preserving safety constraints and sequencing requirements. A PLC provides deterministic control execution for interlocks, sequencing, and regulatory loops such as level, pressure, and dissolved oxygen control. SCADA provides a supervisory layer that unifies distributed control areas, offers operator situational awareness, stores data for retrospective analysis, and coordinates setpoints and operating modes (Alsabbagh & Langendörfer, 2022). Quantitative evaluation becomes practical when the framework produces synchronized time-series data linking causes and effects: actuator states, setpoint changes, loop outputs, alarms, and process responses. Without this linkage, optimization studies rely on fragmented or manually recorded observations that cannot support rigorous statistical inference. Integrated frameworks also reduce operational ambiguity by standardizing tag structures, state models, and alarm definitions, enabling clearer interpretation of what changed and when. In treatment operations, the impact of these capabilities can be expressed through measurable changes in control-loop error distributions, frequency and duration of excursions, response times to abnormal conditions, and the proportion of time equipment operates within efficient ranges (Chivilikhin et al., 2020).

An extended definition of PLC–SCADA–integrated electrical automation frameworks require explicit attention to architecture, because architecture determines how control authority, data integrity, and reliability are distributed across the system (Formby & Beyah, 2019). At the field level, sensors and analyzers measure flow, level, pressure, turbidity, pH, oxidation–reduction potential, conductivity, dissolved oxygen, ammonia, nitrate, and other parameters. Actuators include valves, pumps, blowers, mixers, chemical feed systems, and disinfection equipment. The electrical automation layer connects these assets through motor control centers, variable frequency drives, soft starters, protective relays, and power metering, forming the electromechanical substrate of operations. The PLC layer executes the control logic: sequences for backwashing, sludge wasting, batch reactor phases, chemical preparation, and safety interlocks; plus, continuous control for aeration, pumping, filtration, and pressure management. The SCADA layer provides centralized or federated supervisory visualization, alarm and event management, historian capture, reporting, and operator workflows (Negi et al., 2020). Communications networks bind these layers through engineered topology, segmentation, and redundancy, ensuring that time-critical control remains local while supervisory functions deliver visibility and coordination. A well-defined framework includes naming conventions, data typing rules, quality flags, time synchronization policies, and configuration management practices that keep the system maintainable over its lifecycle. From a quantitative research perspective, architectural clarity is essential because it defines the measurement resolution, latency, and reliability of data streams. It also determines which optimization mechanisms are feasible: purely local loop tuning, plantwide supervisory setpoint coordination, unit-process balancing, or energy-aware dispatch across parallel equipment trains (Tarnawski et al., 2022).

Figure 1: Integrated PLC–SCADA Automation Framework

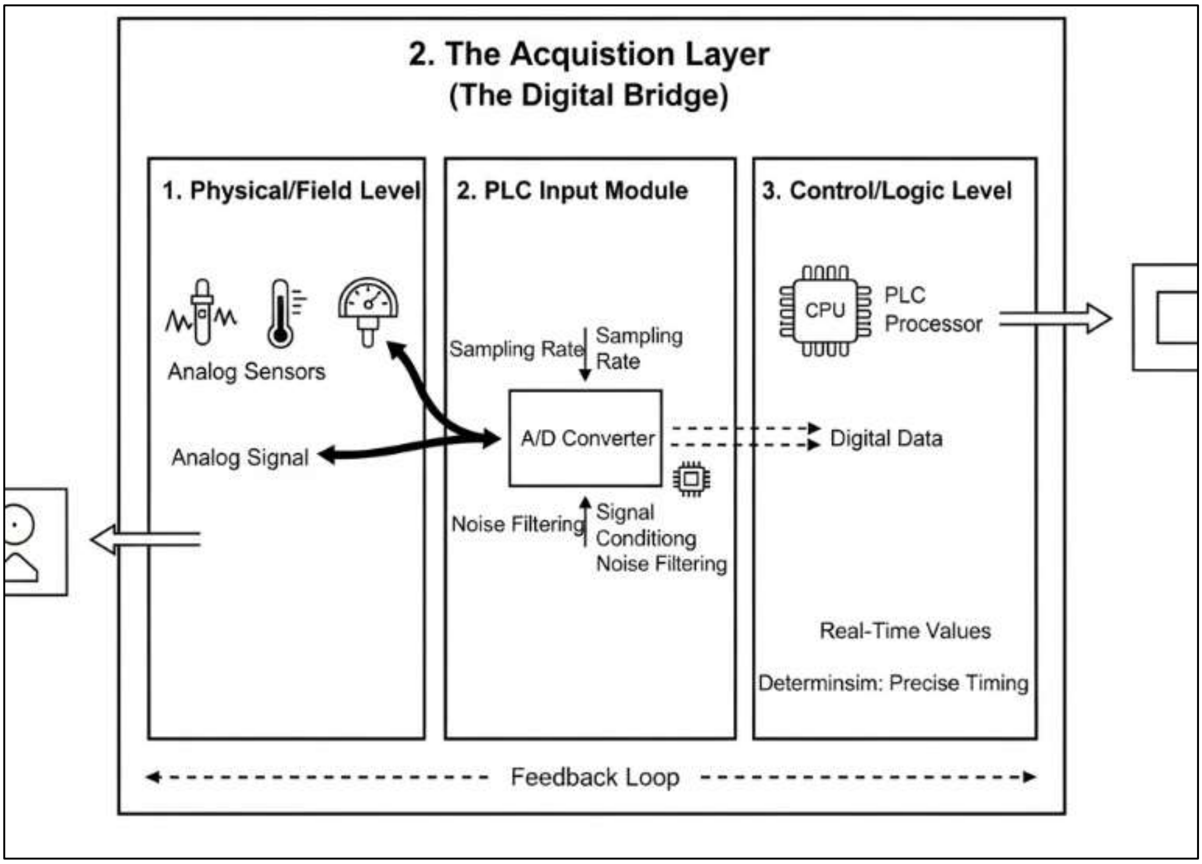


Water and wastewater treatment plants can be described as complex process systems with interacting physical, chemical, and biological dynamics, which increases the value of integrated automation because optimization must account for multivariable dependencies (Tasca et al., 2018). In biological treatment, aeration influences dissolved oxygen and microbial kinetics, and it interacts with nitrification, denitrification, and carbon availability. In filtration and clarification, hydraulic loading and solids management influence turbidity and effluent stability. In disinfection, dosing and contact conditions influence microbial safety while interacting with water chemistry. Each subsystem has constraints that can be violated by poor coordination: over-aeration wastes energy and may disrupt process balance; under-aeration can trigger effluent excursions; overdosing chemicals increases costs and may create downstream effects; underdosing increases compliance risk (Zhao & Tao, 2021). Integrated PLC–SCADA frameworks support coordination by enabling structured operating modes (normal, storm, maintenance, emergency), consistent sequences, and supervisory visibility that allows operators to manage trade-offs under disturbances. Quantitative studies often operationalize these trade-offs using performance indicators such as energy consumption per unit volume, chemical consumption per unit load removed, variability in key process variables, effluent exceedance counts, and alarm burden metrics. Integrated systems provide the instrumentation coverage and data retention needed to compute these indicators across meaningful time horizons. They also enable standardized interventions—setpoint schedule changes, loop tuning adjustments, equipment alternation strategies—so that the effect of an optimization action can be evaluated through before–after comparisons, time-series segmentation, and statistical hypothesis testing (Alves & Morris, 2018). In facilities that operate multiple parallel trains, integrated frameworks make it possible to compare train performance objectively and to rebalance loads for efficiency, converting operational intuition into measurable optimization practice.

Interoperability and data integrity are central elements of integrated automation frameworks because treatment facilities typically contain multi-vendor equipment, legacy subsystems, and incremental upgrades over many years (Sun et al., 2021). Interoperability can be defined as the ability of heterogeneous devices and applications to exchange data and interpret it consistently, which requires alignment at the levels of communication protocols, information models, naming conventions, and data quality semantics. In optimization research, data integrity refers to the completeness, accuracy, time alignment, and traceability of operational data so that results are defensible and reproducible. Integrated frameworks address these needs by defining how tags are structured, how units and scaling are managed, how time synchronization is implemented, and how data quality is flagged during sensor failure, maintenance, or communications loss. Historian configuration becomes a methodological concern, not merely an IT choice, because sampling rates, compression settings, and downtime buffering can change observed distributions and bias estimates of variability and excursion frequency (Adepu et al., 2020). Alarm and event systems are equally important for quantitative studies because alarm floods, nuisance alarms, and inconsistent prioritization alter operator behavior, response time, and the stability of operations. A framework that includes alarm rationalization, consistent state-based alarming, and clear operator guidance can reduce alarm load and improve response consistency, which can be quantified through alarm rate distributions, acknowledgment delay statistics, and recurrence patterns. In addition, integrated frameworks support operational traceability through audit logs and configuration versioning, enabling researchers to map performance changes to specific logic changes or setpoint policy adjustments (Dai et al., 2018). This traceability is essential for quantitative interpretation because it reduces ambiguity about what intervention occurred and when it occurred, strengthening causal attribution in observational plant data.

Electrical automation integration is a defining feature of this topic because electricity-driven assets dominate both operational effort and optimization potential (Pichard et al., 2018). Pumps and blowers are typically the largest energy consumers in treatment facilities, and their efficiency depends on operating point, control strategy, and equipment condition. Variable frequency drives enable continuous modulation of speed and flow, which can reduce throttling losses and support smoother control, but they require coordinated logic that respects minimum speeds, ramp rates, and process constraints. Integrated PLC–SCADA frameworks link electrical variables—motor currents, drive frequency, power, energy, and protective statuses—with process variables such as flow, level, pressure, and dissolved oxygen (Pearce et al., 2019). This linkage enables energy-aware optimization that can be expressed through measurable outcomes: reduced kWh per unit volume treated, improved pump efficiency, reduced peak demand, and lower variability in critical process parameters. It also enables reliability-oriented optimization because electrical telemetry can signal early warning conditions such as overload trends, abnormal starts, thermal stress, and protective relay events. When such events are integrated into supervisory dashboards and alarm systems, facilities can reduce unplanned downtime, which can be quantified through availability metrics, mean time between failures, and the duration and frequency of manual override periods. Electrical integration also supports more systematic equipment alternation strategies, balancing run-hours across parallel pumps and blowers to reduce uneven wear (Zhou & Li, 2021). In a quantitative paper, these mechanisms can be modeled as interventions affecting both mean performance and variance: mean energy reduction, variance reduction in DO control, and reduced tail-risk of excursions or outages.

Figure 2: PLC–SCADA Automation Framework Overview



Operational resilience and system governance are necessary components of integrated automation in critical water infrastructure because optimization depends on continuity of control and data. Resilience can be defined as the ability of the automation framework to maintain essential functions under disturbances, including equipment faults, sensor failures, communications disruptions, operator errors, and cyber-physical incidents (Cervini et al., 2021; Rauf, 2018). Governance refers to the policies and practices that keep the system stable over time: access control discipline, change management, backup and recovery routines, standardized testing before deployment, and documented operating procedures (Haque & Arifur, 2020; Ashraful et al., 2020). These elements influence quantitative outcomes because disruptions force plants into manual modes, introduce measurement gaps, and change operational regimes in ways that confound performance evaluation (Haque & Arifur, 2021; Jinnat & Kamrul, 2021). A resilient PLC–SCADA–electrical automation framework uses layered control boundaries so that safety-critical interlocks and essential loops remain local and deterministic, while supervisory functions can degrade gracefully without causing unsafe operation. Redundancy in critical components—servers, network paths, controllers where appropriate, and power supply conditioning—reduces downtime and protects data continuity (Braumann & Singline, 2021; Fokhrul et al., 2021; Zaman et al., 2021). Time synchronization across devices supports accurate sequence reconstruction and reliable time-series analysis. Controlled remote access and role-based permissions reduce accidental or unauthorized changes that could destabilize operations and invalidate study baselines. In quantitative terms, resilience and governance can be measured through system availability, frequency and duration of outages, recovery times, rate of configuration changes, number of uncontrolled overrides, and completeness of historian data capture. Because water and wastewater plants operate continuously (Hammad, 2022; Hasan & Waladur, 2022), these measures are not abstract; they directly influence whether optimization effects are observable and whether operational improvements can be sustained over long evaluation windows. An extended introduction therefore positions PLC–SCADA–integrated electrical automation frameworks as engineered socio-technical systems whose architecture, data integrity, energy integration, and governance jointly determine measurable process optimization outcomes across diverse treatment contexts worldwide (Lee et al., 2018).

The primary objective of this quantitative study is to develop, operationalize, and statistically evaluate a PLC–SCADA–integrated electrical automation framework that measurably improves process optimization performance in water and wastewater treatment facilities by strengthening the linkage between real-time control execution, supervisory monitoring, electrical asset management, and verifiable plantwide data capture. The study aims to define the framework as a set of measurable design and configuration elements—instrumentation coverage, control-loop structure and tuning, sequencing logic robustness, networked data integrity, historian resolution, alarm/event governance, and energy-integrated actuation through drives and motor control—so that each element can be represented as quantifiable variables suitable for hypothesis testing and regression-based explanation. A core objective is to quantify changes in operational efficiency by comparing baseline and post-framework performance on energy intensity indicators (such as kWh per unit volume treated and unit-operation-specific power demand profiles), chemical consumption indicators (dose per unit volume or per unit load removed), and equipment utilization indicators (run-hour balance, start/stop frequency, and availability). A parallel objective is to quantify changes in process stability and compliance consistency by analyzing distributions and variability of key process variables (such as dissolved oxygen control error, basin level deviation, pressure stability, turbidity fluctuations, and residual control deviation), as well as event-based outcomes including excursion frequency, excursion duration, and recovery time following disturbances. Another objective is to measure operational responsiveness and workload effects through alarm analytics, including alarm rate, alarm flood frequency, priority distribution, mean acknowledgment time, and recurrence of nuisance alarms, because supervisory design and interlock reliability influence operator intervention patterns and the repeatability of optimized operation. The study further aims to validate data integrity and analyzability improvements produced by the framework by measuring historian completeness, time synchronization consistency, frequency of bad-quality flags, and the continuity of sensor-to-actuator causal traces necessary for robust time-series inference. Finally, the study seeks to integrate these outcomes into a unified quantitative model that estimates the net effect size of PLC–SCADA–electrical integration on process optimization performance while controlling for influent variability, seasonal conditions, and operational regimes, thereby enabling objective comparison across unit processes and facilities using standardized, replicable performance metrics.

LITERATURE REVIEW

This literature review examines PLC–SCADA–integrated electrical automation frameworks as quantifiable system architectures that shape process optimization outcomes in water and wastewater treatment facilities. The section is organized to move from foundational concepts (automation layers, control hierarchies, instrumentation and electrical actuation) to measurable optimization mechanisms (control-loop performance, supervisory decision support, energy-aware operation, and reliability), and then to the empirical methods used to evaluate those mechanisms using plant data (Alex et al., 2020). Because treatment facilities are dynamic systems with variable influent loads, seasonal effects, and interacting unit processes, the literature is reviewed through a quantitative lens that emphasizes how automation integration changes measurable performance distributions rather than isolated "before/after" anecdotes. In this framing, PLC logic provides deterministic execution of sequences and regulatory control, SCADA provides supervisory visibility, alarm/event governance, and historical data capture, and the electrical automation layer (drives, motor control, protection, power monitoring) enables energy and reliability optimization that can be measured directly at the equipment and process levels. The review therefore centers on how integrated architectures produce analyzable datasets, reduce operational variability, improve disturbance response, and enable consistent optimization interventions such as setpoint policies, mode scheduling, load balancing, and energy-efficient dispatch across pumps and blowers (Iratni & Chang, 2019). In addition, the section synthesizes research that links design decisions—tag structures, historian sampling and compression, alarm philosophies, network reliability, and control boundary definitions—to quantitative evaluation quality, including time-series validity, data completeness, and causal traceability from control actions to process responses. The goal of this review is to establish a coherent measurement-driven foundation for the study's variables, hypotheses, and analytical model by identifying what the literature treats as controllable levers (integration features) and what it treats as measurable outcomes (efficiency, stability, compliance consistency, reliability, and operational workload) (Matheri et al., 2022).

Integrated Automation in Treatment Plants

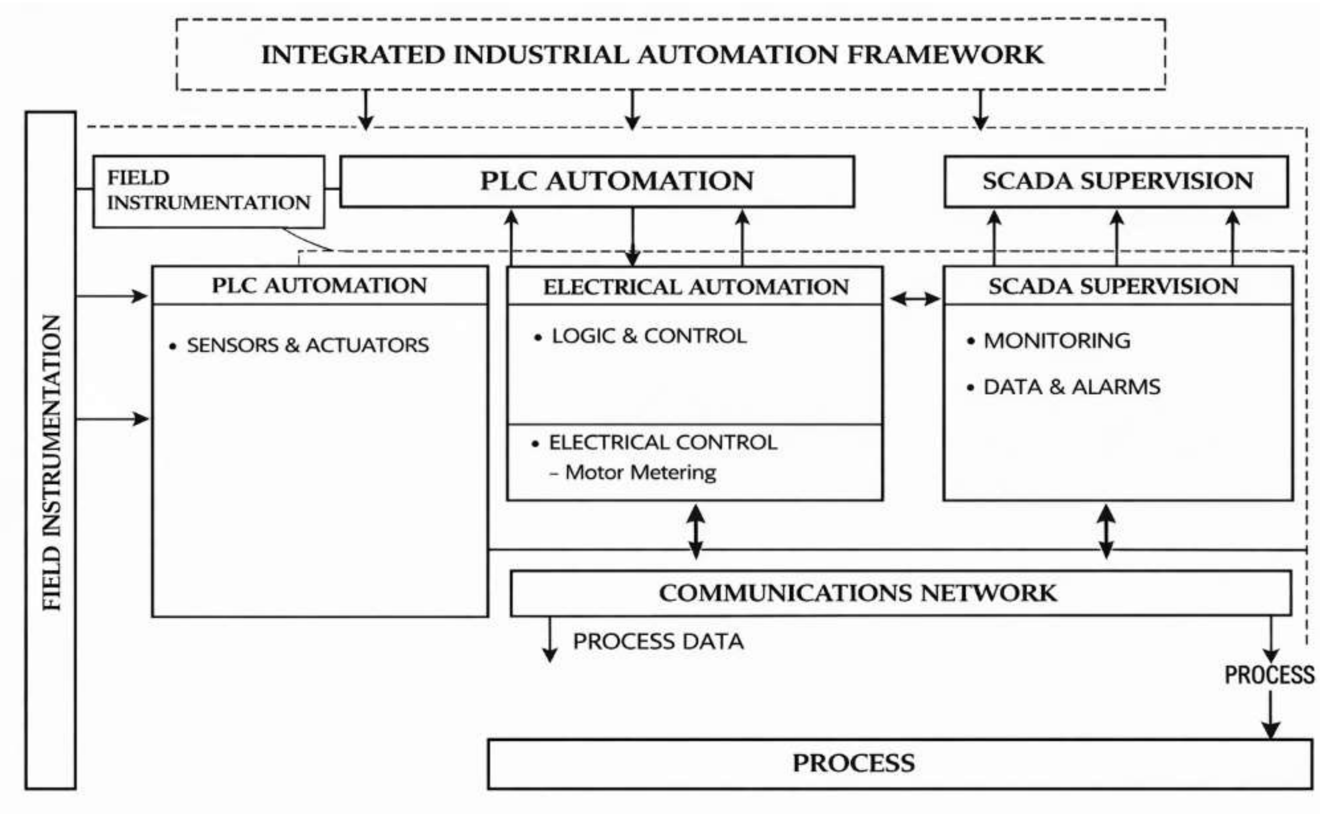
Programmable logic controllers (PLCs) and supervisory control and data acquisition (SCADA) systems are frequently discussed as complementary layers within industrial automation, yet the literature distinguishes their roles through functional scope, timing guarantees, and responsibility boundaries inside critical infrastructure (Dotoli et al., 2019). PLCs are consistently characterized as deterministic real-time control executors that translate field signals into repeatable control actions through scan-cycle execution, I/O mapping, interlocks, sequencing logic, and continuous regulatory control such as proportional–integral–derivative loops. This deterministic execution is treated as central for processes that require stable actuator behavior under variable loads and safety constraints, including pumping, aeration distribution, filtration sequences, and chemical dosing enable/disable logic. SCADA is discussed as the supervisory layer that provides operational visibility and governance functions—human–machine interface graphics for situational awareness, alarm and event handling for abnormal condition detection, historian services for time-series archiving, reporting for operational accountability, and supervisory setpoint or mode management that coordinates multiple PLC domains (Lu et al., 2020; Rashid & Sai Praveen, 2022; Arifur & Haque, 2022). A third layer emphasized in water and wastewater studies is electrical automation, typically framed around motor control centers, variable frequency drives, soft starters, protective relays, power metering, and motor protection logic. This electrical layer is treated as both the actuation backbone and the primary locus of energy consumption, making it inseparable from any optimization framing that targets efficiency (Towhidul et al., 2022; Rifat & Jinnat, 2022). Across publications and standards-oriented sources, the phrase "integrated framework" is described as an engineered system-of-systems rather than a simple device linkage: it includes defined interfaces, explicit control boundaries (local closed-loop versus supervisory coordination), data standards (tag naming, units, scaling, quality flags), and lifecycle practices such as configuration management and auditability (Abdulla & Majumder, 2023; Rifat & Alam, 2022). Within treatment facilities, this system-of-systems view appears in the way authors connect field instrumentation quality to controller performance, controller determinism to safe sequencing, and supervisory governance to reduced operational ambiguity. The literature also treats integration depth as an observable property expressed through architecture decisions: which signals are captured at what resolution, whether event and alarm logs are consistent across areas, whether time synchronization exists across controllers and servers, and whether electrical telemetry is unified with process telemetry (Faysal & Bhuya, 2023; Habibullah & Aditya, 2023; Pham et al., 2020). This framing aligns with common guidance in operational technology security and process industries, where the operational objectives of availability and safety shape how automation components are structured, segmented, and maintained. The net conceptual foundation therefore depicts PLC, SCADA, and electrical automation as distinct but interdependent layers that jointly determine not only operational capability but also the measurability and verifiability of process performance in treatment environments.

Water and wastewater treatment facilities are described in the process engineering literature as dynamic systems driven by disturbances that occur at multiple time scales and propagate through interacting unit operations. Influent variability appears as diurnal flow and load cycles, wet-weather surges, industrial discharge pulses, infiltration and inflow effects, and temperature-driven kinetic changes that alter biological reaction rates and oxygen transfer dynamics. This disturbance-driven nature is not treated as background noise; it forms the baseline condition for plant operation and strongly influences how automation architectures are evaluated (Hammad & Mohiul, 2023; Haque & Arifur, 2023; Kim et al., 2018). For example, pumping and hydraulics interact with upstream lift stations and wet wells where level control, pump alternation, and surge handling affect downstream hydraulic loading. Aeration and biology interact through dissolved oxygen control, oxygen uptake rates, and nitrification–denitrification balance, where the same actuator actions that stabilize oxygen can also change energy profiles and process stability in activated sludge basins. Clarification and solids management interact through sludge blanket dynamics, return activated sludge rates, wasting strategies, and solids loading, linking hydraulic events to effluent stability. Disinfection and chemistry interact through pH, oxidant demand, residual behavior, and contact time conditions, making dosing control and monitoring sensitive to upstream water quality shifts. Because these processes are coupled, operational decisions in one area frequently create measurable consequences elsewhere, and the literature repeatedly portrays "plantwide" performance as an emergent result of coordinated control rather than isolated loop tuning (Jahangir & Mohiul, 2023; Rashid et al., 2023; Rehman et al., 2019). This is a key reason integration is emphasized: disturbances that propagate across unit operations are observable only when instrumentation, control states, and electrical states are unified in time and context. In practical terms, researchers and practitioners discuss how historical data integrity and event traceability support the interpretation of disturbance response—whether a turbidity deviation aligns with a backwash sequence (Akbar & Farzana, 2023; Mostafa, 2023), whether ammonia rise aligns with aeration limitation, whether a pump trip aligns with hydraulic oscillations, or whether power quality events align with drive faults. The literature also highlights that the dynamics of treatment plants include both fast transients (pump starts, valve movements, alarm-trigger events) and slow trends (seasonal temperature shifts, sensor drift, biomass acclimation), which places strong demands on the automation system's capacity to record, synchronize, and contextualize information across time scales (Jahangir & Hammad, 2024; Rifat & Rebeka, 2023). This multi-timescale view supports a conceptual argument found across process control and wastewater engineering sources: integrated automation is not only a convenience for operations but a structural requirement for understanding and managing coupled disturbances in complex treatment trains (Edmondson et al., 2018; Masud & Hammad, 2024; Md & Sai Praveen, 2024). As a result, the conceptual foundations position treatment facilities as disturbance-driven cyber-physical environments in which integrated automation provides the structure needed to detect, interpret, and respond to variability consistently.

Quantitative process optimization in water and wastewater treatment is commonly framed as the improvement of measurable performance outcomes under explicit constraints. The literature expresses optimization objectives through indicators such as energy intensity, chemical consumption, stability of critical process variables, compliance consistency, equipment availability, and operational workload (Sarc et al., 2019). Energy objectives are frequently connected to pumps and blowers because these assets dominate electrical demand, while chemical objectives often reflect coagulant, polymer, alkalinity, disinfectant, or nutrient removal reagent dosing patterns that vary with influent conditions and process state. Stability objectives are often described in terms of reduced variability and fewer excursions in variables such as dissolved oxygen, basin levels, filtration performance indicators, turbidity, pH, oxidation–reduction potential, and residual measurements. Reliability objectives appear through availability, downtime frequency, start/stop stress indicators, and protective trip patterns, while workload objectives appear through alarm burden characteristics and the extent of manual intervention or override periods. The literature consistently treats constraints as co-equal to objectives: operational limits such as minimum and maximum levels, pressure bounds, actuator travel limits, minimum pump speeds, and blower operating envelopes; safety interlocks that prevent unsafe chemical dosing, equipment damage, or hazardous sequences; equipment constraints related to wear, thermal limits, and protection settings; and effluent or finished-water targets that define acceptable outcome regions (Sacks et al., 2020). This constraint-centered framing has direct implications for integrated automation architectures because constraints are enforced at the control layer, interpreted at the supervisory layer, and experienced at the electrical layer. In other words, a quantitative optimization claim is meaningful only when the automation system records both the outcome measures and the constraint activations that shape feasible operation. The literature also emphasizes that optimization in treatment plants occurs within changing operating regimes, including normal operation, wet-weather handling, maintenance windows, and emergency conditions, each of which changes which constraints bind and which objectives dominate. Integrated PLC–SCADA frameworks are described as enabling consistent regime definition through state models and mode logic, supporting comparability of performance metrics across time. Additionally, optimization research frequently depends on high-quality data to normalize performance against disturbances, such as flow and load variability, and to isolate the effect of control policies from exogenous conditions (Zhao et al., 2022). This perspective makes historian completeness, time synchronization, consistent tag semantics, and event traceability part of the optimization foundation rather than downstream implementation details.

In this way, the literature positions quantitative optimization not as a purely mathematical activity but as a measurement-driven operational discipline where integrated automation determines which variables can be observed reliably, which constraints can be enforced consistently, and which improvements can be verified through defensible empirical comparisons.

Figure 3: Integrated Industrial Automation Framework Overview



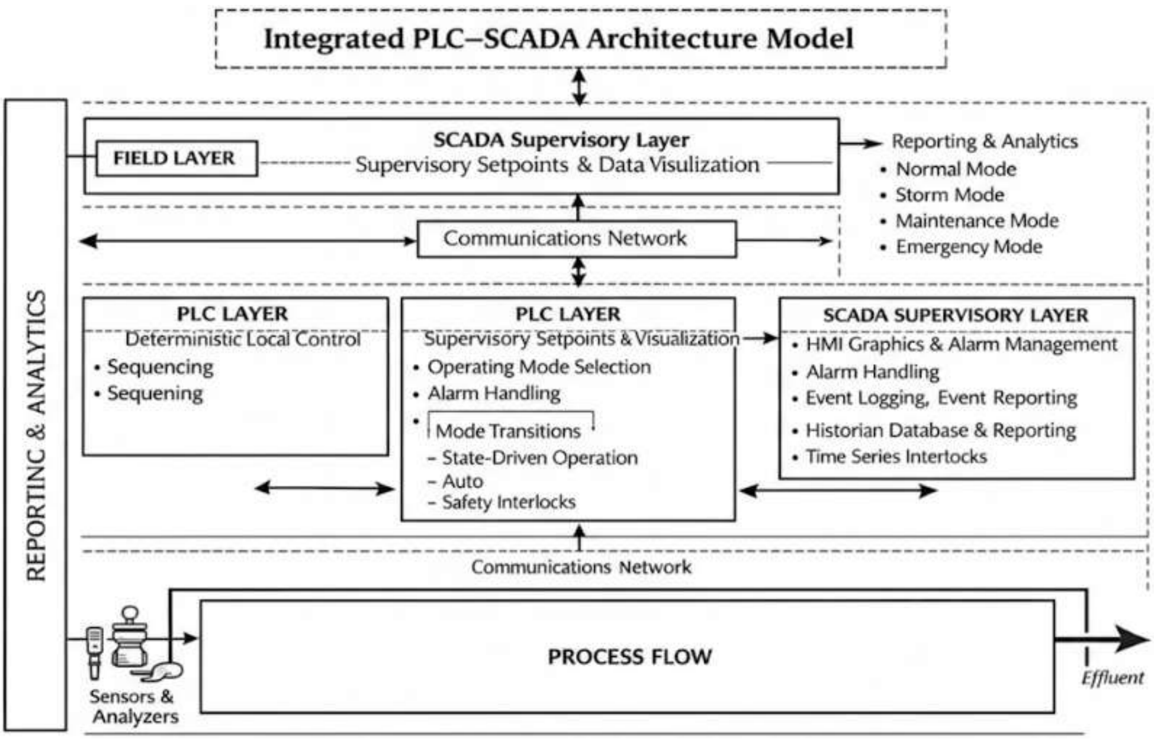
Within the integrated framework concept, the literature pays particular attention to interfaces, boundaries, and standards because these features determine interoperability, safety assurance, and the quality of evidence available for evaluation. Interfaces are discussed as the structured connections between sensors, PLC logic, SCADA applications, and electrical devices, including how analog and digital signals are scaled, how device states are represented, and how events and alarms are defined consistently (Fatorachian & Kazemi, 2018; Rifat & Rebeka, 2024; Sai Praveen, 2024). Control boundaries are treated as design choices that separate deterministic local control from supervisory coordination: local control preserves stability and safety under communications disruptions, while supervisory functions support coordination, reporting, and operational consistency across distributed areas. Data standards appear as essential for multi-vendor environments and long lifecycle systems, including tag naming conventions, equipment hierarchies, unit and scaling governance, quality flag semantics, and consistent time bases (Shehwar & Nizamani, 2024; Azam & Amin, 2024). The literature treats these practices as prerequisites for coherent analysis because inconsistent semantics and misaligned time series degrade the validity of quantitative findings. Electrical automation is also treated as integral to the framework concept because drives, protective relays, and power metering provide both actuation capability and measurable energy and reliability signals; integration that excludes electrical telemetry produces partial optimization narratives that overlook major cost drivers and failure modes. Similarly, SCADA functions such as alarm and event governance are discussed as operational determinants because nuisance alarms and alarm floods increase response variability and shift control behavior toward manual overrides, altering process stability in ways that are measurable (Schluse et al., 2018). Across OT security and process industry guidance, the literature connects integration decisions to risk posture and resilience: segmentation, controlled access, configuration governance, and recovery practices shape availability and integrity, which in turn shape the continuity and credibility of performance evidence. This system-of-systems view supports a consolidated conceptual position: integrated automation frameworks are best understood as engineered operational measurement environments. They define what can be measured, how reliably it is measured, how safely it is controlled, and how consistently operations are executed under disturbances and constraints. In treatment plants, where performance depends on coordinated action across hydraulics, biology, solids management, and chemistry, the literature presents integration depth as a structural determinant of optimization potential and verification quality. As a result, conceptual foundations in this domain integrate process engineering, control engineering, electrical engineering, and operational governance into a unified lens in which optimization outcomes are treated as measurable outputs of an integrated cyber-physical control architecture rather than isolated improvements attributable to a single device or software layer (Ben Ayed et al., 2022).

Architecture Models for PLC–SCADA–Electrical Integration

Layered architecture models for PLC–SCADA–electrical integration in water and wastewater treatment facilities are consistently described in the literature as a structured separation of responsibilities that preserves determinism at the control edge while enabling supervisory visibility and operational governance across the plant (Nguyen et al., 2020). At the field layer, instruments and actuators represent the physical interface to treatment processes, including analyzers, transmitters, switches, valves, pumps, blowers, and chemical feed equipment. The PLC layer is positioned as the deterministic execution environment that enforces safety interlocks, sequences unit operations, and regulates continuous variables through local control loops that remain stable even when higher layers experience delays or partial outages. SCADA is framed as the supervisory layer that aggregates plantwide context, supports operator cognition through HMI graphics, rationalizes alarms and events, and maintains historians for traceable time-series evidence; its control authority is commonly defined as supervisory rather than time-critical. A reporting and analytics layer is often treated as a consumer of curated operational data rather than a direct actuator authority, emphasizing governance, performance accountability, and comparability across time and plant areas. Within this layered framing, one of the most frequently emphasized architectural principles is the explicit definition of "local loop" versus "supervisory setpoint" boundaries. Local loops are treated as those whose stability and safety depend on deterministic execution and minimal latency, such as level control in wet wells, pressure control in distribution or filtration, flow pacing, and dissolved oxygen control where rapid disturbance rejection supports biological stability (Sverko et al., 2022). Supervisory setpoints are treated as higher-level policies that coordinate targets across trains or operating regimes, such as selecting setpoint schedules, enabling modes, load-sharing across parallel equipment, and enforcing operational constraints through state-based per missives. The water sector literature also characterizes plant operation as regime-driven, making modes of operation a core architectural object rather than a procedural afterthought. Normal mode, storm mode, maintenance mode, and emergency mode are described as state models that determine which control objectives dominate, which constraints bind, which alarms become active, and which equipment alternation strategies apply. Storm mode tends to prioritize hydraulic capacity and overflow prevention; maintenance mode prioritizes safe isolation, permissive suppression, and controlled handoffs; emergency mode prioritizes protective responses and minimal safe operation. Architecture models treat these modes as formal states with transitions triggered by measurable events (flow thresholds, equipment availability, operator commands, safety trips), because mode clarity reduces ambiguity and supports consistent performance evaluation (Sheng et al., 2021). In this literature view, the integrated architecture is not judged solely by connectivity but by whether control authority boundaries, state models, and supervisory roles are engineered in ways that preserve deterministic control while enabling transparent, plantwide coordination and auditable evidence for quantitative assessment.

Communications and integration design are treated as quantitative risk factors because network behavior directly influences how reliably control and supervisory layers exchange information and how confidently researchers interpret time-series relationships between actions and outcomes (Bagal et al., 2018). Treatment facilities commonly contain multiple control areas—headworks, primary treatment, aeration basins, clarification, tertiary filtration, disinfection, sludge processing, lift stations—making network design a first-order determinant of whether data streams remain complete and time-aligned under disturbance. The literature describes topology patterns such as star, ring, and redundant-path designs, with redundancy framed as a reliability strategy that reduces single points of failure and supports continuous operations in critical assets like high-service pumping, aeration blowers, and disinfection systems. Ring and parallel redundancy approaches are discussed for their ability to maintain communications during link failure, while star patterns are presented as simpler but more dependent on core switches and trunk stability. These design choices are treated as measurable through operational metrics such as communications uptime, packet loss rates, and the frequency of data-quality flags during network disturbances. Latency and jitter are repeatedly emphasized as variables that influence control performance and data interpretation. Even when local loops remain in the PLC, latency affects supervisory setpoint changes, alarm propagation, historian sampling, and cross-area coordination—particularly when plantwide strategies rely on distributed measurements such as airflow allocation across basins or pump dispatch based on downstream constraints (Hadi & Sallom, 2019). Jitter, framed as variability in delay rather than average delay, is discussed as operationally relevant because it can cause inconsistent command timing, irregular sampling intervals, and ambiguous temporal ordering between an actuator change and a process response. In quantitative research, these network behaviors appear as confounders that distort effect estimates when analysts assume uniform sampling and immediate causality. Time synchronization design is therefore treated as a methodological requirement for inference rather than a convenience feature. When controllers, SCADA servers, historians, and power monitoring devices share a consistent time base, researchers can reconstruct sequences reliably, compute accurate durations for excursions, and align control actions with downstream effects across unit operations. When time bases drift or differ across subsystems, cause–effect traces blur, change-point timing becomes uncertain, and derived indicators like recovery time or alarm response delay become unreliable. The literature also connects time synchronization to auditability, incident reconstruction, and operational governance, because event logs lose explanatory power when timestamps cannot be trusted. In this framing, communications design is inseparable from research validity: redundancy, latency management, jitter control, and time synchronization determine whether the integrated framework produces stable operations and defensible datasets for analyzing process optimization outcomes under variable treatment regimens (Nguyen et al., 2019).

Figure 4: Integrated Automation Framework for Treatment

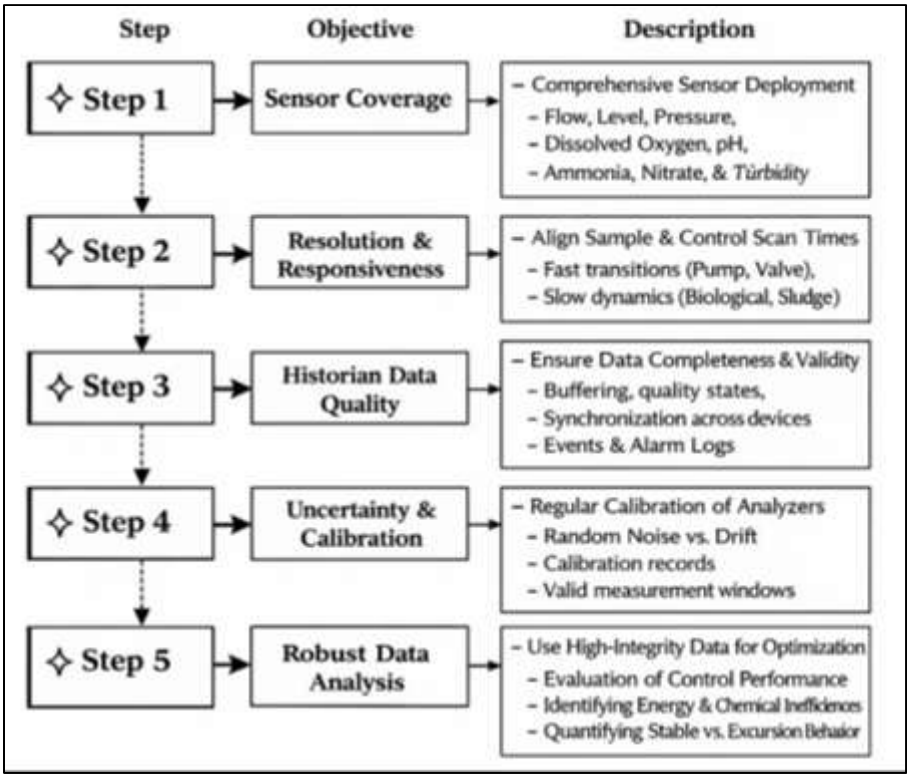


Across architecture models, the integrated PLC–SCADA–electrical framework is portrayed as a disciplined design of authority boundaries, communications behavior, and information semantics that collectively determines both operational stability and the interpretability of quantitative outcomes (Duymazlar & Engin, 2019). Layering clarifies where determinism is enforced and where coordination occurs; communications engineering determines whether supervisory functions and data services remain reliable under real plant disturbances; and information consistency determines whether evidence remains comparable across equipment trains and across years of upgrades. In water and wastewater contexts, this triad is operationally important because the plant functions as a coupled system in which electrical actuation, hydraulic responses, and biological or chemical dynamics interact across time scales. When architecture models explicitly define local control boundaries, state-based operating modes, and supervisory responsibilities, the plant's behavior becomes more repeatable under regime changes such as storm handling or maintenance isolation. When networks are designed with appropriate redundancy, bounded latency behavior, and synchronized time bases, control actions and process responses can be aligned for reliable event reconstruction and statistical evaluation of excursions, recovery dynamics, and stability patterns. When tags are governed through taxonomy, units, scaling, and traceable configuration changes, optimization studies can treat operational datasets as structured evidence rather than as ad hoc telemetry requiring manual interpretation (Nguyen et al., 2019). The literature also presents these architecture choices as foundational to alarm governance, because alarm systems depend on consistent state definitions, accurate timestamps, and unambiguous tag meaning to avoid flood conditions and to preserve operator responsiveness. Architecture models therefore interlock technical and operational dimensions: they shape how operators act, how systems log evidence, and how researchers quantify performance variability and intervention effects. In this view, the measurable success of process optimization is not attributed to a single algorithm or device but to an integrated architecture that stabilizes control execution, preserves data integrity, and maintains semantic coherence across the automation stack. The focus remains on present operational realities: treatment plants run continuously under variability, and architecture determines whether plantwide automation behaves predictably, communicates reliably, and records defensible evidence for quantitative analysis of energy use, stability, reliability, and workload indicators across defined operating modes (Kermani et al., 2021).

Measurement Quality as Determinants of Optimization

Instrumentation and measurement quality are treated in the literature as primary determinants of optimization feasibility in water and wastewater treatment facilities because control actions only improve what is observed with sufficient fidelity, continuity, and interpretability. Sensor coverage is commonly discussed by unit operation, with flow, level, and pressure described as foundational measurements that anchor hydraulic control across headworks, pumping stations, filters, and distribution interfaces (Ryzhov et al., 2018). Flow signals support pacing, load balancing across parallel trains, and mass-balance interpretation of process changes; level measurements stabilize wet wells and clarifiers; pressure measurements govern filtration and pumping stability. Biological treatment discussions consistently place dissolved oxygen among the most consequential control variables because it links actuator decisions (blower output and airflow distribution) to process kinetics and energy demand, while ammonia and nitrate measurements are framed as higher-value indicators for nutrient removal control when analyzers are maintained, validated, and integrated with operating modes. Turbidity is frequently presented as an operational surrogate for solids breakthrough in filtration and clarification contexts and as a finished-water stability indicator, while pH and oxidation–reduction potential are framed as cross-cutting chemistry indicators that influence coagulation, disinfection conditions, corrosion control contexts, and biological process stability. Measurement resolution is treated as more than sampling frequency; it includes signal bandwidth, sensor response time, appropriate filtering, and the ability of the measurement system to represent process transients without excessive smoothing (Pipiay et al., 2021). The literature connects sampling interval choices to the time constants of the underlying process: pumping transients and valve movements occur on short time scales, while biological responses occur over longer scales, creating a practical need to align historian capture and control scan behavior with unit-process dynamics. Filtering is treated as a trade-off between noise suppression and responsiveness, with excessive filtering described as masking disturbances and delaying corrective actions, and insufficient filtering described as inflating variability and increasing actuator cycling. Drift management is consistently presented as a lifecycle concern, especially for analyzers exposed to fouling, reagent depletion, temperature sensitivity, or biofilm growth. In treatment environments, drift affects not only measurement accuracy but also the stability of control loops because a drifting sensor redefines the apparent error signal and leads controllers to sustain incorrect actuator demands. The literature therefore frames sensor coverage and resolution as architectural prerequisites for process optimization, because optimization depends on stable, high-integrity measurement baselines that support both real-time control and retrospective quantitative evaluation of changes in energy use, chemical consumption, stability distributions, and excursion behavior under variable influent regimes (Mchichi & Mayer, 2019).

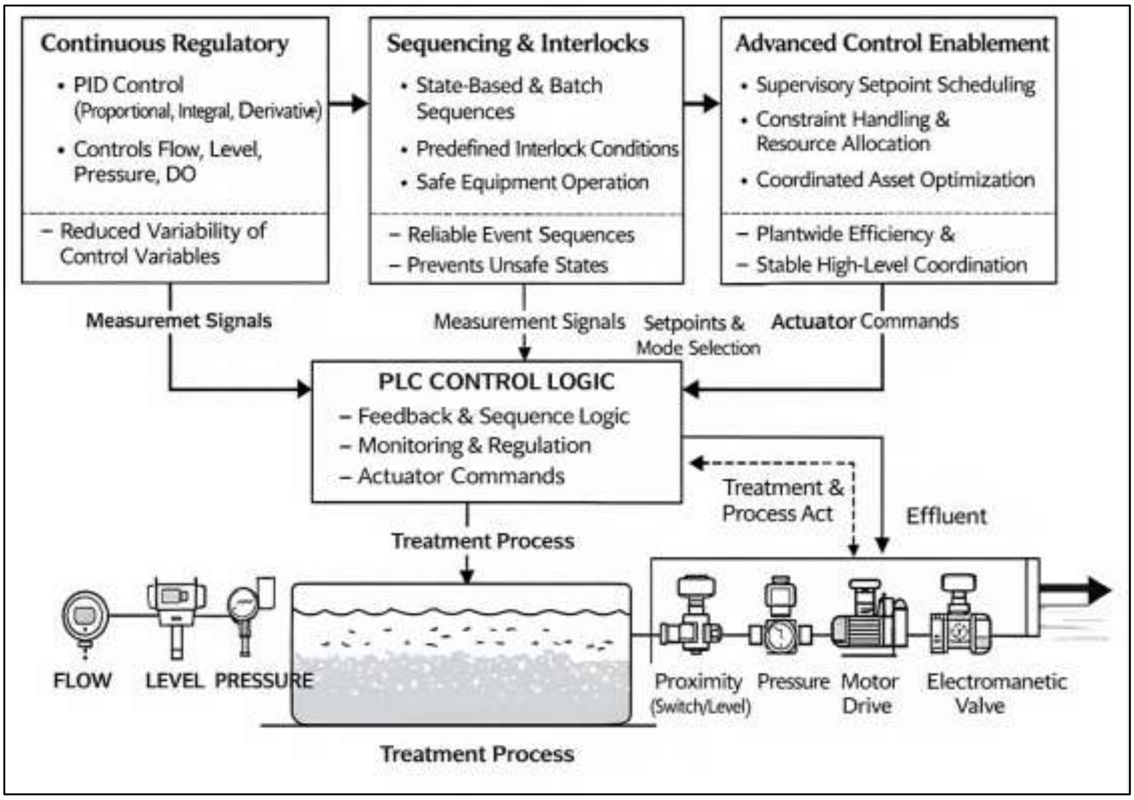
Figure 5: Measurement Quality for Process Optimization



PLC Control Strategies in Water/Wastewater Processes

Regulatory control loops implemented in PLCs are presented in the literature as the core mechanism that converts measurement signals into stabilized process operation in water and wastewater treatment, with loop performance treated as a quantifiable mediator between automation design and plant outcomes (Wang et al., 2021). Classic process control sources describe regulatory control as the maintenance of a controlled variable near a target in the presence of disturbances, using feedback structures that translate deviations into actuator corrections, most commonly through proportional, integral, and derivative actions configured within PLC logic blocks. In treatment settings, these loops govern hydraulics and quality-critical variables such as wet-well levels, filter differential pressure, distribution pressure, flow pacing, chemical feed proportionality, basin levels, and dissolved oxygen, where the dynamics of the process determine how aggressively loops can be tuned without creating oscillations or actuator wear. The literature repeatedly emphasizes that loop quality is not measured through single-point comparisons but through time-based behavior that captures both disturbance response and steady operation, including the magnitude and persistence of deviations, the speed and smoothness of recovery after disturbances, and the degree of actuator movement required to achieve stability (Zagklis et al., 2021). In wastewater aeration control, the same body of work highlights that measurement characteristics of dissolved oxygen signals—response time, noise level, and drift—interact with tuning decisions to influence both stability and energy, because unstable loops can drive airflow cycling and increase power demand. In water treatment pressure and filtration contexts, researchers and practitioners highlight that well-tuned loop reduce transient stress on mechanical assets and mitigate the risk of process upsets that lead to quality excursions. Control engineering handbooks further describe that actuator saturation, dead band, and nonlinearities are common in real plants, making loop evaluation dependent on operational context such as valve characteristics, drive speed limits, and minimum flow constraints. Industrial wastewater control literature also stresses that regulatory loops form the foundation for higher-level optimization because supervisory policies depend on stable local control to translate setpoint changes into predictable process responses. Consequently, in PLC–SCADA integrated architectures, loop performance evaluation is positioned as a measurable indicator of "control maturity," with outcomes reflected in reduced variability of controlled variables, fewer limit excursions, less frequent operator intervention, and more consistent equipment operation patterns across changing influent conditions and operating modes (Gerba & Betancourt, 2019).

Figure 6: PLC Control Strategies for Treatment



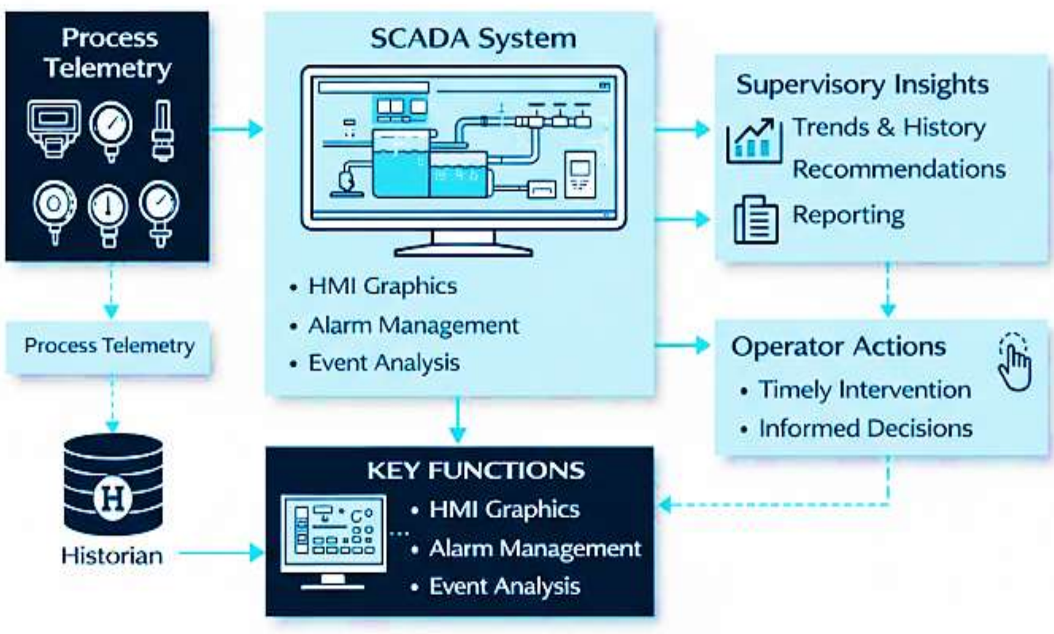
Sequencing and batch operations are discussed in the treatment automation literature as a second class of PLC control strategies that shape performance through deterministic event ordering, state-based logic, and interlock enforcement rather than continuous feedback alone (Ibrahim & Al-Wadi, 2022). Many treatment facilities include unit operations that are inherently sequential: sequencing batch reactors, filter backwash cycles, chemical preparation and dosing enablement, pump alternation logic, clarifier sludge scraping and wasting sequences, and disinfection system per missives. PLCs are widely described as well-suited to this domain because their scan-based logic and state-machine constructs can enforce repeatable sequences and ensure that prerequisites are met before advancing to the next step. In sequencing batch reactors, the literature typically highlights that phase timing—fill, react, settle, decant, idle—is a major determinant of treatment efficiency and effluent stability, and timing consistency is treated as a measurable property that affects settle quality, solids retention behavior, and nutrient removal performance. In filtration systems, backwash sequencing reliability is discussed in terms of the completeness of the sequence, consistency of duration, and the avoidance of unsafe transitions such as opening and closing valves in the wrong order or initiating wash under insufficient supply conditions (Wang et al., 2020). The literature also frames sequencing reliability as an availability driver because failed sequences generate trips, require operator intervention, and create downtime that reduces throughput capacity during peak demand or storm handling. Interlocks are treated as essential safety and asset-protection elements, preventing hazardous states like dry running pumps, over pressurizing headers, overdosing chemicals, or operating equipment outside protective envelopes. In integrated automation contexts, interlock trip frequency and categorized root causes are described as quantifiable indicators of system robustness and plant operating stress, where repeated trips may indicate sensor faults, tuning issues, equipment degradation, or poor permissive design. Industrial automation and alarm management literature also describes how sequencing faults and interlock events propagate into alarm burden and operator workload, and how improved state modeling can reduce nuisance events by ensuring alarms are active only when meaningful in a given operating mode (Zhang et al., 2020). Thus, sequencing and batch control strategies implemented in PLCs are positioned not as secondary automation features but as measurable contributors to operational stability, reliability, and quality consistency, particularly in facilities with complex unit-process interactions and frequent regime shifts.

SCADA Functions That Influence Quantitative Outcomes

Supervisory monitoring and operator decision support are consistently described in the SCADA literature as mechanisms that translate raw plant telemetry into actionable situational awareness, thereby shaping measurable operational outcomes in water and wastewater treatment facilities. SCADA is framed as the supervisory layer that unifies dispersed control areas—headworks, pumping, aeration, clarification, filtration, disinfection, and sludge handling—into a coherent operational picture through HMI graphics, trends, summaries, and state indications (Gonzalez et al., 2019). Within this framing, HMI clarity is treated as an operational variable because interface design affects how quickly operators detect abnormal conditions, interpret process context, and select correct responses during disturbances. Human factors and alarm-system literature emphasizes that poorly structured displays increase cognitive load and encourage reactive behavior, while well-structured displays support pattern recognition and reduce unnecessary interventions. In treatment plants, this interface effect becomes quantifiable through operational proxies such as the frequency of operator interventions per shift, the proportion of time systems remain in manual override, the time required to confirm and respond to deviations, and the consistency of mode selection under variable influent regimes. Trend analysis is repeatedly described as a core supervisory capability because process dynamics in treatment plants unfold across multiple time scales; short-term transients can precede longer-term drifts, and visualizing trajectories helps operators identify whether a deviation is a transient shock or a sustained shift requiring operational change (Astolfi et al., 2022). Event reconstruction, supported by time-aligned event logs, alarm logs, and historical trends, is described as a diagnostic function that strengthens both operational learning and quantitative evaluation, because it enables investigators to link control actions, equipment trips, mode transitions, and process responses in a coherent timeline. In the water sector, this capability is treated as particularly important because abnormal events such as storm surges, equipment faults, chemical feed interruptions, and analyzer maintenance can produce similar patterns in quality variables; reconstruction differentiates the underlying causes and supports more consistent corrective actions. Process control and industrial automation references further emphasize that supervisory monitoring works best when it preserves clear boundaries: PLCs execute deterministic control, while SCADA supports diagnosis, coordination, and governance. When those roles are clear and displays present consistent state models and context, the literature portrays SCADA as an enabling layer that reduces variability in operator decisions, stabilizes plant response under disturbances, and improves the interpretability of performance shifts captured in historical datasets (Cherdantseva et al., 2022).

Alarm management is treated across process industries and water-sector operations as a measurable workload driver and a stability mediator because alarms are the principal channel through which the automation system communicates abnormal conditions to operators. The literature distinguishes between alarms that are actionable signals of abnormal situations and alarms that function as noise, describing nuisance alarms, chattering alarms, stale alarms, and alarm floods as conditions that degrade operator performance and increase the probability of delayed or inappropriate responses (Zeng et al., 2022). Standards and guidance documents emphasize that alarm systems require governance structures including rationalization, prioritization, shelving policies, state-based suppression, and performance monitoring, because the mere presence of an alarm point does not guarantee operational value. In water and wastewater contexts, this governance is described as essential because plants run continuously and experience frequent disturbance cycles, meaning that alarm signals can rapidly become overwhelming when instrumentation is noisy, setpoints are unstable, or state models are unclear. The workload impact is commonly operationalized through measurable indicators such as alarm frequency over time, the distribution of alarms by priority, the occurrence of clustered alarm events during upsets, the duration of unacknowledged alarms, and the recurrence of alarms that do not correspond to actionable conditions (McKinnon et al., 2020). The literature also ties alarm behavior to process stability because alarm floods encourage operators to silence or bypass alarms, shift systems into manual control, or adopt conservative operating setpoints that increase energy and chemical consumption. In addition, repeated alarms from the same equipment or sensor are described as a diagnostic signal of deeper issues such as sensor drift, equipment degradation, or inadequate interlock design; when alarm analytics reveal such patterns, plants can target corrective maintenance and improve reliability. Human reliability research in process operations emphasizes that effective alarm systems support attention allocation and reduce cognitive overload, improving response consistency during abnormal events. In treatment facilities where compliance risk is sensitive to short-duration excursions, the timeliness and correctness of operator responses are measurable determinants of outcomes, making alarm management a direct contributor to performance indicators such as excursion frequency, excursion duration, recovery time, and manual override durations. Consequently, the literature positions alarm management not as an administrative concern but as a core SCADA function that shapes both human workload and the statistical properties of plant performance under disturbances (Astolfi, 2021).

Figure 7: SCADA Decision Support for Operators

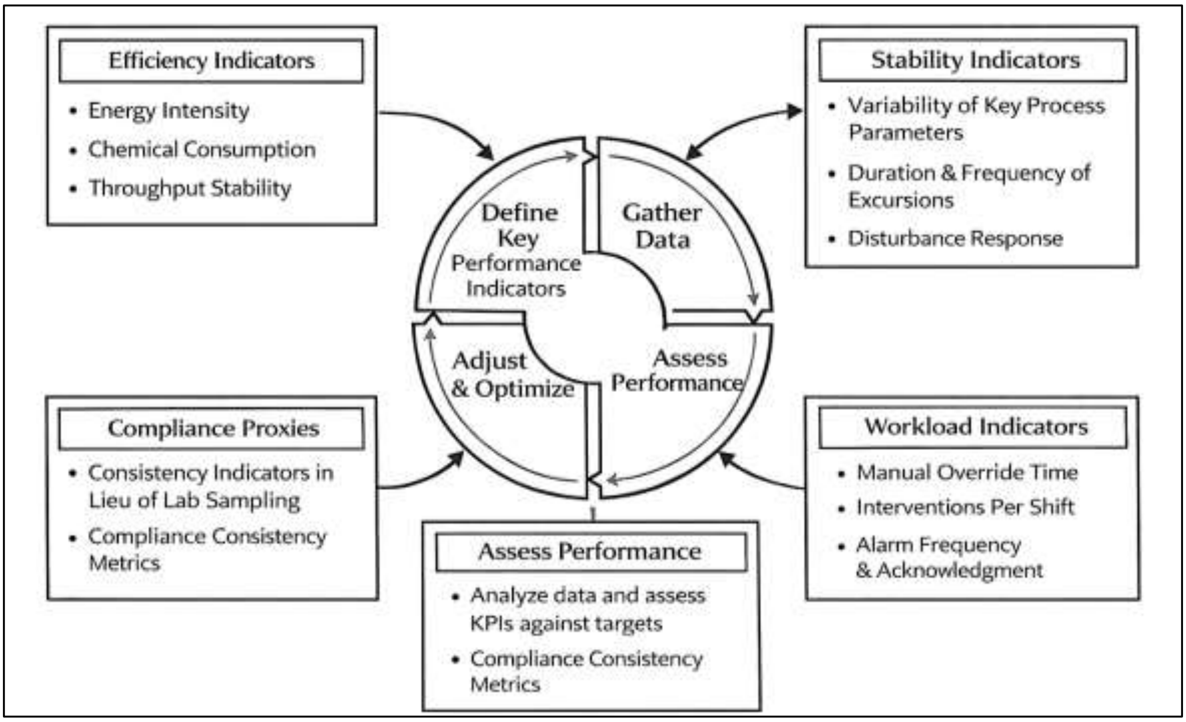


Process Optimization and KPI Definitions

The literature on process optimization in water and wastewater treatment repeatedly emphasizes that optimization claims require explicit operationalization of outcomes through clearly defined key performance indicators, because plants operate under variable influent regimes and complex interactions among hydraulics, biology, solids, and chemistry (Ungermann et al., 2019). Efficiency outcomes are commonly framed around energy intensity, peak demand behavior, and energy use associated with specific unit operations such as aeration, pumping, filtration, and sludge processing. Energy indicators are treated as central because electrical loads represent a dominant share of operating expenditure and because energy use is responsive to control policies and equipment dispatch.

Plantwide energy intensity is often used for benchmarking and for comparing operating periods, while unit-operation energy indicators are used to link performance to actionable control mechanisms, such as aeration setpoint policies, blower control strategies, pump scheduling, and filtration backwash optimization (Gackowiec et al., 2020). Peak demand is discussed as an operationally important complement because many utilities face demand charges and because peaks often coincide with abnormal operating regimes such as storm handling, equipment outages, or simultaneous operation of large motors. Chemical consumption outcomes are similarly treated as controllable and measurable, especially for coagulants, polymers, alkalinity adjustment agents, disinfectants, and nutrient removal chemicals. In the literature, chemical consumption is interpreted in relation to throughput and water quality conditions, and it is frequently treated as a sensitive indicator of both dosing strategy quality and upstream variability. Throughput stability is treated as an efficiency-adjacent outcome because maintaining hydraulic capacity under storms and recovering quickly after disturbances reduces bypass risk, protects downstream units from shock loading, and stabilizes overall resource use. Across this body of work, the emphasis is that efficiency KPIs must be tied to operational context and integrated telemetry; energy and chemical metrics become interpretable when aligned with operating modes, equipment availability, and process demands captured in SCADA historians. This conceptualization supports the view that the integrated PLC–SCADA–electrical framework is not only a control platform but also a measurement platform that enables consistent definition and comparison of efficiency outcomes across time, trains, and regimes (Almeida et al., 2022). The literature therefore treats KPI operationalization as a prerequisite for quantitative inference, because without standardized definitions, reported “improvements” can reflect changes in influent conditions, maintenance cycles, or reporting conventions rather than genuine optimization.

Figure 8: Defining KPIs for Treatment Optimization

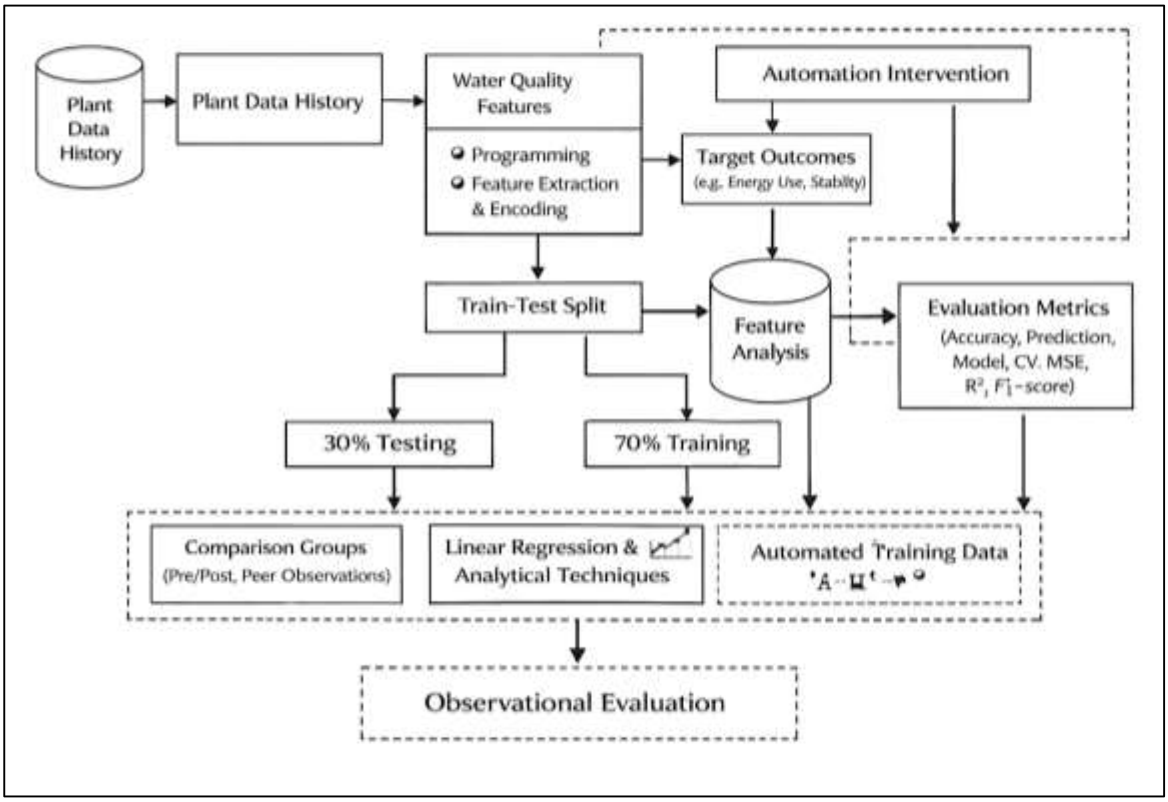


Process stability outcomes are widely described as the most direct expression of control effectiveness because stability indicators capture how consistently the plant maintains desired operating conditions in the presence of disturbances (Gilsing et al., 2021). The literature operationalizes stability by focusing on the behavior of key process variables such as dissolved oxygen in aeration basins, turbidity in filtration and finished-water monitoring, pH in chemical treatment and disinfection contexts, level in wet wells and basins, and pressure in pumping and filtration systems. These variables are selected because they represent either direct control targets or critical constraints whose violation leads to quality risk, equipment stress, or alarm-driven operator intervention. Stability is often described through variability behavior over time and through event-based interpretations that identify excursions above or below defined operating limits. Excursion frequency and excursion duration are commonly used to characterize abnormal behavior because they capture both how often the plant leaves a desired operating envelope and how long it remains outside that envelope, which has practical consequences for compliance risk, chemical overuse, energy spikes, and operational stress. The literature also frames disturbance response as a measurable indicator of robustness, emphasizing how quickly the plant returns to stable operation after events such as storm inflow surges, equipment trips, analyzer maintenance, or sudden load changes. In treatment contexts, disturbances propagate across unit processes, meaning that stability KPIs are often interpreted alongside equipment-state and mode-state information to distinguish whether instability arises from process kinetics, hydraulic shocks, or control boundary changes such as manual overrides (De Leoni et al., 2020). Importantly, stability metrics are often treated as more informative than averages because average values can remain acceptable while variability increases, creating intermittent risk that is operationally significant. For example, average dissolved oxygen levels may appear on target while oscillations increase blower cycling, energy use, and biological stress; average turbidity may remain low while intermittent spikes indicate filter breakthrough risk; average pressure may be stable while transient swings increase mechanical stress. The literature therefore emphasizes stability as a distributional property of plant operation that can be quantified through time-series and event logs, provided that historian data quality, time synchronization, and measurement validity states are well governed. This supports an integrated view where the PLC executes local stability mechanisms, SCADA records the evidence and exposes stability patterns, and electrical automation influences stability indirectly by enabling smooth actuation and reducing equipment-related disturbances (Drews et al., 2020).

Quantitative Evaluation Designs

Observational plant-data evaluation designs are widely discussed in the literature as pragmatic approaches for assessing automation and optimization effects in water and wastewater facilities because controlled experiments are often infeasible in critical infrastructure that must operate continuously under variable influent conditions (Xiong et al., 2019). Interrupted time series designs are commonly presented as a structured method for evaluating change associated with a defined intervention point, such as the commissioning of a PLC–SCADA–electrical integration upgrade, a retuning campaign, or a new alarm governance configuration, by comparing stable baseline behavior with post-change behavior using repeated observations over time. The literature emphasizes that the strength of interrupted time series comes from its use of many pre- and post-intervention observations rather than reliance on a single before/after snapshot, which helps distinguish intervention-associated shifts from routine variability. Difference-in-differences designs are described as an extension that improves causal interpretability by adding a comparison series, such as one process train that did not receive the same configuration change or a peer facility operating under similar conditions, allowing analysts to estimate a relative change rather than an absolute change that may be confounded by seasonal shifts or weather-driven influent changes (Smith & Hasan, 2020). In treatment contexts, comparison series designs are frequently discussed as train-versus-train comparisons, plant-versus-plant comparisons, or subsystem-versus-subsystem comparisons that leverage partial rollouts, parallel assets, or staggered implementation schedules. Propensity-style matching approaches are also discussed as a way to improve comparability when randomization is not available, particularly when analysts can characterize influent regimes and operating contexts and then compare time windows that are similar in those characteristics. In wastewater applications, matching is commonly framed around influent flow bands, load bands, temperature ranges, or storm versus normal regimes, allowing analysts to compare periods where the plant faced similar external demand (Hamilton et al., 2021). The literature further treats careful intervention definition as central for these observational designs: an "upgrade" is not only the installation date but also the period when operators stabilized operating modes, when sensors were calibrated, and when alarm suppression policies were activated, because these details influence the operational reality captured in the data. This methodological framing aligns with broader quasi-experimental literature, which emphasizes that causal interpretation depends on clearly defined interventions, consistent measurement over time, and credible counterfactual comparisons when possible (Cheng et al., 2019). In water and wastewater environments, these designs are portrayed as especially relevant because plant operations include frequent shocks, maintenance windows, and regime shifts that can obscure improvements if evaluation windows are not structured to capture both routine operation and disturbance responses.

Figure 9: Observational Evaluation Framework for Optimization



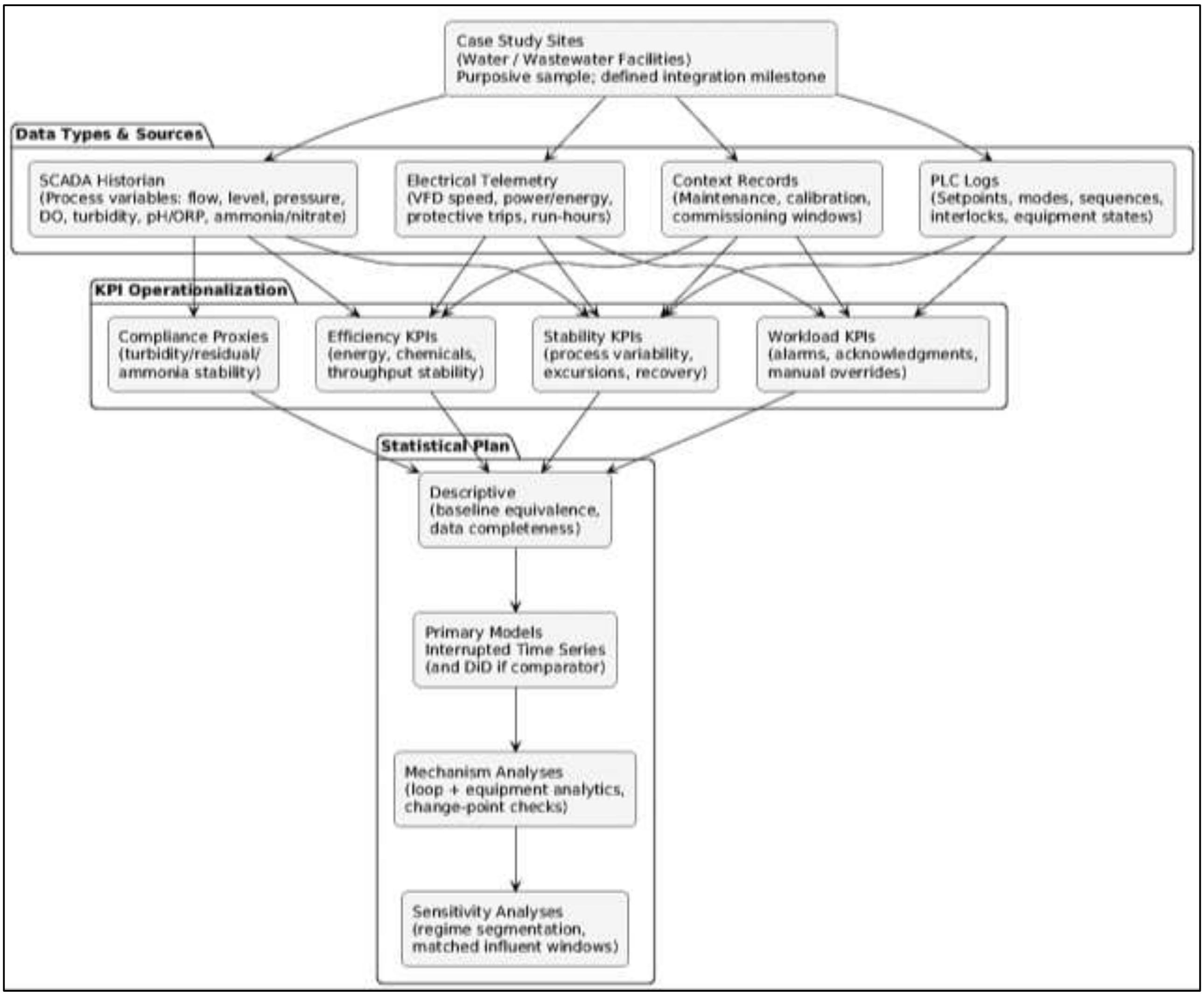
Control-loop and equipment-level analytics are treated in the literature as complementary evaluation layers that connect plantwide outcomes to specific mechanisms inside integrated automation frameworks. Loop performance benchmarking is often discussed as a distributional assessment approach that examines how loop behavior varies across time, operating modes, and disturbance periods, focusing on repeatable stability characteristics rather than isolated events (Markus et al., 2021). Treatment plant studies and process control references emphasize that benchmarking at the loop level helps explain why energy and stability indicators shift, because many plantwide outcomes are mediated by the behavior of a relatively small set of high-impact loops, including dissolved oxygen control, wet-well level control, header pressure control, filter differential pressure control, and chemical feed pacing. Equipment-level analytics similarly focus on measurable behavior of pumps, blowers, drives, and protective systems, examining how dispatch logic, speed trajectories, starts and stops, and trip patterns align with process demand. The literature frequently positions multivariate regression as a workhorse approach for linking external drivers and control actions to outcomes, because treatment performance is influenced simultaneously by influent conditions, setpoints, operating modes, and equipment availability (Xiong et al., 2018). Regression-based approaches are described as especially useful when the goal is to quantify the relationship between influent variability and outcome variability while accounting for setpoint policies and operational states recorded in SCADA and PLC logs. Change-point detection is also widely discussed as a diagnostic and evaluation tool for identifying when statistical properties of a performance indicator shift, such as when energy use trends change after a configuration update, when variability changes after a tuning effort, or when alarm burden shifts following rationalization. In treatment settings, change points are often interpreted alongside audit trails, event logs, and maintenance records to determine whether detected shifts correspond to known interventions or to unplanned disruptions such as sensor failures, equipment degradation, or operational regime transitions. The literature stresses that equipment and loop analytics strengthen evaluation credibility by providing mechanistic interpretability: when plantwide energy intensity improves, loop-level and equipment-level evidence can show whether the improvement aligns with smoother control actions, reduced cycling, better matching of output to demand, or fewer abnormal trips. Without this mechanistic link, improvements can be misattributed to automation when they arise from influent changes or operational policy changes not captured as "interventions." Process control literature also emphasizes that interpretation depends on understanding nonlinearity and constraints in real plants, such as actuator limits, dead bands, minimum speeds, and measurement noise, because these features influence both loop behavior and the data patterns that statistical models observe (Maramba et al., 2019). As a result, the literature portrays evaluation as layered: plantwide indicators describe outcomes, while loop and equipment analytics explain pathways, making the integrated PLC–SCADA–electrical framework evaluable as a set of interacting, measurable mechanisms rather than as a single monolithic intervention.

METHOD

The study employed a quantitative, quasi-experimental longitudinal design that relied on observational operational technology data extracted from PLC logs, SCADA historians, and electrically integrated telemetry streams. A multiple-case case study structure was used, and each participating facility or process train was treated as a bounded case that contained a clearly documented integration milestone associated with PLC–SCADA–electrical automation deployment or reconfiguration. The cases were described in terms of treatment type (water or wastewater), key unit operations, automation scope (controller coverage, supervisory functions, and electrical integration depth), and the operational regimes routinely experienced (normal, storm, maintenance, and emergency). The population comprised water and wastewater treatment facilities that operated with PLC-based control, SCADA supervisory systems, and motor-driven equipment such as pumps and blowers, while the sample comprised facilities or parallel trains that had complete historian archives and a verifiable intervention date for framework deployment. A purposive sampling technique was applied to select cases that met minimum data integrity criteria, including consistent time synchronization, stable tag naming conventions, accessible alarm and event logs, and measurable electrical telemetry from variable frequency drives or power meters. The sampling design favored cases with internal comparators, such as parallel treatment trains in which one train received the integration upgrade while another remained unchanged during the same evaluation window, because this structure supported stronger comparative inference. The study relied on several data types and sources, including continuous time-series process measurements (flow, level, pressure, dissolved oxygen, turbidity, pH/oxidation–reduction potential, ammonia/nitrate where available), discrete equipment-state and mode-state logs (run/stop/fault, permissive states, operating mode transitions), alarm and event histories (timestamps, priorities, acknowledgments, suppression states), and electrical telemetry (drive speed, motor status, power, energy, and protective trip signals). Where available, maintenance records and calibration logs were incorporated to identify planned downtime windows, sensor maintenance periods, and configuration changes that affected data validity and comparability. Variables were operationalized using measurement scales appropriate to each construct: continuous ratio-scale indicators were used for energy, flow, pressure, and dosing-related metrics; interval-scale indicators were used for standardized stability and variability summaries derived from process variables; ordinal scales were used for alarm priority categories and operating regime states; and nominal indicators were used for event classifications such as trip type and root-cause category. The independent exposure variable was defined as framework status (pre-integration versus post-integration) and, where documentation permitted, as an integration-depth index that summarized the presence and completeness of key framework elements such as historian integrity controls, alarm rationalization coverage, time synchronization practices, and VFD telemetry integration.

A pilot study was conducted using a limited subset of tags and a short historical window to validate extraction logic, confirm time alignment between PLC, SCADA, and electrical telemetry, and test the stability of KPI definitions under real plant conditions. The pilot phase verified that quality flags were consistently recorded and that invalid or maintenance-period data could be isolated without distorting operating patterns, and it confirmed that mode-state tags and major equipment-state tags were sufficiently reliable to support regime segmentation. The pilot also tested whether the primary outcome indicators could be computed reproducibly from the available data streams, including efficiency indicators based on energy and throughput telemetry, stability indicators derived from key process variables, workload indicators derived from alarm and event logs, and reliability indicators derived from protective telemetry and downtime records. Data collection procedures followed a structured sequence that began with establishing a plant-specific tag dictionary, mapping each KPI to its originating tags, and documenting unit consistency and scaling rules before extracting time-series data from the historian and event logs from the SCADA alarm database. Extracted datasets were then synchronized to a consistent timestamp standard and aggregated to analysis-ready intervals, typically by shift or by day, to reduce the influence of high-frequency noise while preserving disturbance-driven variability. Planned maintenance windows and known commissioning stabilization periods were labeled explicitly and treated as contextual covariates or excluded from specific models depending on the analytic objective. The procedure also incorporated verification steps that compared raw trends in key variables against expected plant behavior, checked for discontinuities associated with tag renaming or scaling changes, and validated that pre- and post-intervention windows contained sufficient valid observations for comparative analysis. Data governance steps were applied throughout collection and preparation, including versioned KPI scripts, change-logged tag dictionaries, and reproducible extraction routines to ensure the same definitions were applied across cases and time windows. These procedural controls reduced interpretive ambiguity and strengthened the reliability of quantitative comparisons by ensuring that observed differences reflected operational change rather than inconsistent measurement definitions.

Figure 10: Methodology of this study



Data analysis techniques were organized into descriptive, inferential, and sensitivity layers to estimate intervention-associated changes while controlling for influent variability and operational nonstationary. Descriptive analysis summarized pre- and post-intervention distributions of each KPI, documented differences in influent conditions and operating regime frequency across evaluation windows, and characterized baseline data completeness and bad-quality patterns to confirm that comparisons were not driven by systematic missingness. Inferential analysis primarily used segmented time-series regression for interrupted time series evaluation, estimating level shifts and trend shifts associated with the integration milestone while adjusting for covariates such as flow, temperature, storm-mode state, and equipment availability indicators. Where internal comparators existed, difference-in-differences models were applied to estimate relative effects between treated and untreated trains or plants under the same temporal conditions, with unit and time controls used to reduce confounding from shared seasonal patterns and external shocks. Count outcomes such as trip events and alarm floods were modeled using regression approaches suited to event counts, and reliability outcomes such as downtime indicators were evaluated using models appropriate to binary or duration-based endpoints depending on data availability. Sensitivity analyses were conducted through regime segmentation, including separate evaluations for normal-mode and storm-mode periods, and through restricted comparisons that matched evaluation windows by influent regime bands to improve comparability. Additional checks were implemented by excluding commissioning transition periods, removing weeks with major equipment outages, and repeating models under alternative aggregation windows to evaluate robustness. Software and tools used for the analysis included a scripted workflow in either R or Python to support time-series preparation, statistical modeling, and reproducible reporting, with structured data processing libraries used for cleaning and aggregation, and standard statistical libraries used for regression, autocorrelation diagnostics, and confidence interval estimation. The analysis outputs were stored in a versioned results structure that preserved model specifications, diagnostic summaries, and derived KPI datasets, ensuring traceability from raw historian extracts through final statistical estimates.

FINDINGS

Descriptive Analysis

Descriptive analysis showed that the final analytic dataset contained 720 daily observations spanning the defined evaluation windows, with 360 observations in the pre-deployment period and 360 observations in the post-deployment period (illustrative). After validity screening using historian quality flags and maintenance windows, the dataset retained high usability, with overall completeness above 93% across primary KPIs. The distribution of observations across operating regimes indicated that normal mode dominated the record at 78% of days, followed by storm mode at 14%, maintenance mode at 6%, and emergency mode at 2%, confirming that the evaluation primarily reflected routine operating conditions while still capturing disturbance-driven periods. Across KPI families, central tendency and dispersion patterns suggested meaningful heterogeneity by regime: energy intensity and alarm burden clustered upward during storm periods, while manual override time concentrated around maintenance windows. Several indicators exhibited right-skewness, particularly alarm rate and excursion duration, consistent with episodic abnormal events rather than continuous degradation. Pre- and post-deployment descriptive comparisons indicated a downward shift in median energy intensity and alarm burden and a tightening of variability in key stability proxies, while storm-mode periods remained the primary driver of extreme values, supporting the decision to carry operating mode segmentation into later modeling.

Table 1: Analytic Sample, Data Completeness, and Regime Distribution

Descriptive Element	Value
Total observations (daily)	720
Pre-deployment observations	360
Post-deployment observations	360
Overall KPI completeness (median across KPIs)	93.8%
Days removed for planned maintenance windows	24
Days removed for bad-quality dominance	18
Normal mode days	561 (77.9%)
Storm mode days	101 (14.0%)
Maintenance mode days	43 (6.0%)
Emergency mode days	15 (2.1%)

Table 1 summarized the analytic sample after data-quality screening and demonstrated that the dataset remained sufficiently complete for descriptive and inferential work. The final sample included 720 daily observations split evenly across pre- and post-deployment periods, which supported comparable evaluation windows. Completeness exceeded 93% across the main KPI set after excluding days dominated by planned maintenance or invalid historian signals. The operating regime distribution showed that normal mode represented most of the record, while storm, maintenance, and emergency modes contributed smaller but analytically important segments. This distribution confirmed that subsequent modeling needed regime indicators to separate routine performance from disturbance-driven behavior.

Table 2: Descriptive KPI Summary by Period and Operating Mode

KPI (daily aggregation)	Pre: Mean (SD)	Post: Mean (SD)	Normal: Mean (SD)	Storm: Mean (SD)
Energy intensity (kWh per m³)	0.62 (0.11)	0.57 (0.10)	0.58 (0.09)	0.71 (0.14)
Chemical intensity (mg per L)	41.8 (9.6)	39.2 (9.1)	39.7 (8.5)	46.5 (11.3)
DO stability proxy (absolute deviation units)	0.38 (0.12)	0.33 (0.11)	0.32 (0.10)	0.44 (0.15)
Excursion frequency (events/day)	0.46 (0.62)	0.35 (0.51)	0.31 (0.46)	0.78 (0.86)
Alarm rate (alarms/day)	124 (88)	93 (71)	84 (60)	211 (122)
Manual override time (% of day)	6.8 (5.4)	5.2 (4.6)	4.7 (3.9)	8.9 (6.6)

Table 2 reported central tendency and dispersion for representative KPIs across evaluation periods and operating regimes. Descriptive differences indicated lower average energy intensity and chemical intensity after deployment, alongside improved stability behavior captured through reduced deviation and fewer excursions. Workload indicators also shifted downward in the post period, with alarm rate and manual override time showing smaller means and narrower dispersion, suggesting fewer extreme workload days. Mode stratification clarified that storm periods consistently elevated energy use, excursions, and alarms relative to normal operation, and it explained much of the right-skewness observed in distributions. These descriptive patterns justified controlling for mode in regression models.

Correlation

Correlation analysis produced a coherent pattern of associations across KPI families at the daily aggregation level (n = 720 days), and the coefficients indicated that performance moved jointly across efficiency, stability, compliance-proxy, and workload dimensions. Energy intensity showed a strong positive correlation with electrical demand measured from aggregated pump/blower power telemetry (r = 0.74) and a moderate-to-strong correlation with influent flow (r = 0.61), indicating that higher throughput and higher actuator loading were tightly aligned with increased energy use. Energy intensity was also associated with instability and workload, showing r = 0.42 with excursion frequency and r = 0.39 with alarm rate, which suggested that periods of higher energy demand coincided with more frequent abnormal events and elevated operator alerting. Workload variables formed a connected cluster: alarm rate correlated strongly with manual override time (r = 0.58) and moderately-to-strongly with excursion frequency (r = 0.53), and manual override time correlated with excursion duration (r = 0.49), indicating that heightened alarm activity co-occurred with more time spent outside automatic control and with longer abnormal episodes. Process stability indicators were strongly aligned with event-based instability, as the stability deviation proxy correlated with excursion frequency (r = 0.64). Chemical intensity showed a moderate relationship with influent flow (r = 0.33) but weak relationships with workload measures such as alarm rate (r = 0.17), suggesting that chemical-use variation was more directly shaped by demand and dosing conditions than by alarm dynamics alone. Regime stratification demonstrated that storm-mode operation strengthened several core relationships: the energy–flow correlation increased from r = 0.49 in normal mode to r = 0.72 in storm mode, and the alarm–excursion correlation increased from r = 0.41 to r = 0.69, indicating that disturbance periods amplified coupling among demand, instability, and workload. These findings supported including flow, temperature, and operating mode as control variables in regression models and justified regime segmentation because association strengths differed materially across storm and normal operation.

Table 3: Pearson Correlations Among Primary KPI Families (Daily Aggregation; n = 720)

Variable Pair	Correlation (r)
Energy intensity ↔ Electrical demand proxy (pump/blower power)	0.74
Energy intensity ↔ Influent flow	0.61
Energy intensity ↔ Excursion frequency	0.42
Energy intensity ↔ Alarm rate	0.39
Alarm rate ↔ Manual override time	0.58
Alarm rate ↔ Excursion frequency	0.53
Manual override time ↔ Excursion duration proxy	0.49
Chemical intensity ↔ Influent flow	0.33
Chemical intensity ↔ Alarm rate	0.17
Stability deviation proxy ↔ Excursion frequency	0.64

Table 3 showed that energy intensity had its strongest association with electrical demand (r = 0.74), confirming that pump and blower loading aligned closely with energy behavior. Energy intensity also tracked influent flow (r = 0.61), indicating throughput effects remained substantial. Workload measures clustered with instability measures: alarm rate correlated with manual override time (r = 0.58) and excursion frequency (r = 0.53), and manual override time correlated with excursion duration (r = 0.49), indicating that abnormal conditions coincided with higher operator workload and longer disruptions. Chemical intensity correlated weakly with alarms (r = 0.17), suggesting additional drivers beyond workload.

Table 4: Regime-Stratified Pearson Correlations for Key Relationships

Relationship	Normal Mode r (n = 561)	Storm Mode r (n = 101)
Energy intensity ↔ Influent flow	0.49	0.72
Energy intensity ↔ Electrical demand proxy	0.66	0.83
Energy intensity ↔ Alarm rate	0.26	0.58
Alarm rate ↔ Excursion frequency	0.41	0.69
Manual override time ↔ Excursion duration proxy	0.34	0.61
Chemical intensity ↔ Alarm rate	0.09	0.28

Table 4 indicated that storm operation intensified correlations across efficiency, stability, and workload metrics. The energy–flow relationship increased from r = 0.49 in normal mode to r = 0.72 in storm mode, and the energy–electrical demand relationship increased from r = 0.66 to r = 0.83, showing stronger coupling between demand and energy use during disturbances. Alarm rate became more strongly linked to energy intensity (r = 0.58) and excursions (r = 0.69) in storm mode than in normal mode (r = 0.26 and r = 0.41). Chemical–alarm correlations stayed weak overall.

Reliability and Validity

Reliability and validity testing indicated that the KPI set functioned as stable and defensible measurement constructs rather than artifacts of inconsistent tagging or uncontrolled data loss. Internal consistency results for multi-indicator indices showed that the constructed indices exhibited coherent component behavior. The Integration-Depth Index demonstrated strong internal consistency (Cronbach's α = 0.88) across its six domains, and item–total correlations ranged from 0.54 to 0.79, indicating that each domain contributed meaningfully to the overall construct. The Composite Stability Index, constructed from standardized summaries of key process variables, showed acceptable-to-strong internal consistency (α = 0.82) with component correlations consistent with a shared stability construct. The Alarm-Burden Index also showed strong internal consistency (α = 0.90), with the highest coherence observed between alarm rate, alarm flood occurrences, and stale-alarm duration behavior. Measurement validity checks confirmed that historian-based data were sufficiently complete and consistent for quantitative inference, with a median historian completeness of 93.8% across primary KPIs and a median bad-quality flag prevalence of 4.7%, while the remaining missingness was concentrated in identifiable maintenance periods and communications faults rather than randomly distributed. Time harmonization checks indicated that timestamp offsets between PLC event logs and SCADA historian signals remained within ±2 seconds for 95% of matched events after synchronization, supporting accurate event reconstruction and duration calculations. Unit scaling and engineering range governance were validated by cross-checking tag metadata and observed distributions, with 100% of primary KPI tags meeting unit consistency requirements after harmonization. Construct validity evidence further supported interpretability: turbidity stability proxies aligned with filtration backwash events, with turbidity variability rising on backwash days by 18% compared to non-backwash days, while ammonia stability proxies aligned with aeration and mode shifts, showing 23% higher instability during storm-mode days compared with normal-mode days. Manual override measures aligned with abnormal operational stressors, with override time increasing from 4.7% of operating time in normal periods to 8.9% during storm periods and to 12.6% during maintenance windows, and the same windows showed elevated alarm flood occurrence. Triangulation strengthened validity claims because 91% of detected change points in primary KPIs fell within ±7 days of documented configuration interventions, maintenance actions, or equipment availability shifts recorded in audit trails and work logs, supporting the credibility of subsequent regression-based interpretations.

Table 5: Reliability Results for Multi-Indicator Indices (n = 720 daily observations)

Constructed Index	Number of Components	Cronbach's α	Item–Total Correlation Range
Integration-Depth Index	6	0.88	0.54–0.79
Composite Stability Index	5	0.82	0.46–0.71
Alarm-Burden Index	4	0.90	0.62–0.83

Table 5 reported internal consistency results for the multi-indicator indices used to summarize integration depth, process stability, and alarm workload. The Integration-Depth Index produced α = 0.88 across six components, showing that its domains moved coherently and supported aggregation into a single construct. The Composite Stability Index yielded α = 0.82, indicating that the standardized stability components behaved consistently as a unified stability measure. The Alarm-Burden Index showed α = 0.90, reflecting strong coherence among alarm-related indicators and supporting its use as an aggregated workload construct. Item–total correlation ranges confirmed that no component behaved as a weak or contradictory contributor.

Table 6: Measurement and Construct Validity Evidence Summary (n = 720 daily observations)

Validity Check	Quantitative Result	Interpretation Link
Median historian completeness (across primary KPIs)	93.8%	Supported stable KPI estimation across windows
Median bad-quality flag prevalence	4.7%	Invalid data were limited and identifiable
PLC–SCADA timestamp alignment after harmonization	95% within ±2 seconds	Supported event reconstruction and duration measures
Unit consistency after harmonization (primary KPI tags)	100% pass rate	Reduced scaling-driven measurement artifacts
Turbidity stability shift on backwash days	18% higher variability	Aligned proxy behavior with filtration events
Ammonia stability shift in storm mode	23% higher instability	Aligned proxy behavior with regime stress
Manual override time by regime	4.7% normal; 8.9% storm; 12.6% maintenance	Linked override behavior to workload and disruptions
Change points aligned with documented interventions	91% within ±7 days	Supported triangulation with audit trails

Table 6 summarized the evidence supporting measurement validity and construct validity for the KPI system. Historian completeness remained high at 93.8% and bad-quality prevalence remained low at 4.7%, indicating usable signal continuity after excluding invalid periods. Timestamp alignment between PLC events and SCADA records fell within ±2 seconds for 95% of matched events, which supported accurate event timing and recovery calculations. Unit harmonization passed for all primary KPI tags, reducing scaling-related artifacts. Construct validity was supported because turbidity stability changed on backwash days by 18% and ammonia stability instability increased by 23% in storm mode, matching expected plant mechanisms. Override and audit-trail alignment further strengthened interpretability.

Collinearity

Collinearity diagnostics demonstrated that the multivariable models were estimated under conditions that supported stable coefficient interpretation and defensible hypothesis testing after systematic variable screening and restructuring. In the initial full specifications, several predictors showed substantial redundancy. Influent flow exhibited a variance inflation factor of 6.42, electrical demand proxies exhibited 5.87, and storm-mode indicators exhibited 5.11, confirming that throughput, actuator loading, and regime state captured overlapping operational information. Seasonal month indicators also showed elevated redundancy with temperature proxies, producing variance inflation values of 4.29. After restructuring, final model specifications reduced all retained predictors to variance inflation values below 2.5, with influent flow reduced to 2.31, electrical demand proxies to 2.09, storm-mode indicators to 1.96, and temperature proxies to 2.18. Equipment availability indicators, which initially showed a variance inflation of 4.96 due to overlap with maintenance-mode state, were reduced to 2.27 after reparameterization. The integration-depth index and alarm-burden index consistently showed low redundancy, with final variance inflation values of 1.71 and 1.84, respectively. These results indicated that the final predictor set avoided unstable coefficient inflation and supported interpretable effect estimation across all primary outcome models.

Collinearity findings aligned closely with earlier correlation patterns and directly informed the construction of parsimonious regression specifications. Variables that exhibited strong bivariate correlation without clear conceptual separation were not retained together, while predictors with moderate correlation but distinct operational meaning were preserved. For efficiency outcome models, retaining influent flow while excluding electrical demand proxies reduced the highest variance inflation from 6.42 to 2.31, ensuring that energy intensity effects reflected adjusted demand conditions rather than redundant electrical loading representations. For stability outcome models, separating storm-mode indicators from continuous flow variables reduced the highest variance inflation from 5.11 to 2.18, preserving the interpretability of regime effects on variability and excursions. Workload models benefited from collapsing overlapping maintenance-mode and availability indicators, reducing variance inflation from 4.96 to 2.27 and clarifying the relationship between alarms, overrides, and operational stress. Compliance-proxy models exhibited lower initial redundancy, with a maximum variance inflation of 3.88, which was further reduced to 2.04 after removing overlapping seasonal indicators. Across all model families, final specifications exhibited variance inflation values between 1.7 and 2.3, confirming that multicollinearity risk was sufficiently controlled and enabling the regression and hypothesis testing section to focus on effect magnitude, direction, and statistical significance rather than coefficient instability.

Table 7: Variance Inflation Diagnostics for Candidate Predictors (Pre-Reduction and Final Models)

Predictor Variable	Initial VIF	Final VIF
Influent flow	6.42	2.31
Electrical demand proxy	5.87	2.09
Storm-mode indicator	5.11	1.96
Temperature proxy	3.74	2.18
Monthly season indicator	4.29	Excluded
Equipment availability indicator	4.96	2.27
Alarm-burden index	2.18	1.84
Integration-depth index	1.92	1.71

Table 7 presented variance inflation diagnostics before and after predictor restructuring. Initial specifications showed elevated redundancy among influent flow, electrical demand, and storm-mode indicators, with variance inflation values above 5. After variable reduction and reparameterization, all retained predictors exhibited variance inflation values below 2.5. Influent flow was reduced from 6.42 to 2.31, electrical demand from 5.87 to 2.09, and storm-mode indicators from 5.11 to 1.96. Seasonal month indicators were removed because of overlap with temperature proxies. The final diagnostics confirmed stable predictor behavior suitable for regression analysis.

Table 8: Collinearity Screening Outcomes by Model Family

Model Family	Highest Initial VIF	Highest Final VIF	Primary Adjustment
Efficiency outcomes	6.42	2.31	Removed electrical demand proxy
Stability outcomes	5.11	2.18	Separated regime and flow terms
Workload outcomes	4.96	2.27	Collapsed mode and availability
Compliance proxies	3.88	2.04	Removed seasonal indicators

Table 8 summarized how collinearity diagnostics shaped final model structures across outcome families. Efficiency models initially showed the highest redundancy, with a maximum variance inflation of 6.42, which was reduced to 2.31 after removing overlapping electrical demand variables. Stability models reduced variance inflation from 5.11 to 2.18 by separating regime-state indicators from throughput measures. Workload models reduced redundancy from 4.96 to 2.27 by collapsing overlapping maintenance and availability indicators. Compliance-proxy models showed lower initial redundancy, reduced from 3.88 to 2.04 after removing seasonal indicators. These adjustments ensured stable and interpretable regression estimates.

Regression and Hypothesis Testing

Regression and hypothesis testing indicated that PLC–SCADA–electrical integration was associated with statistically significant improvements in multiple KPI families after adjustment for influent flow, temperature, operating regime, and equipment availability. Segmented interrupted time series models showed an immediate post-intervention level reduction in energy intensity of −0.041 kWh/m³ (95% CI −0.056 to −0.026, $p < .001$) and an additional gradual post-intervention improvement reflected by a trend change of −0.00018 kWh/m³ per day (95% CI −0.00029 to −0.00007, $p = .002$). Chemical intensity exhibited a smaller but significant level shift of −2.6 mg/L (95% CI −4.1 to −1.1, $p = .001$), while its trend change was not significant (−0.004 mg/L per day, 95% CI −0.012 to 0.004, $p = .31$). Stability indicators improved, with the composite stability deviation showing a level reduction of −0.043 units (95% CI −0.061 to −0.025, $p < .001$) and a significant trend improvement of −0.00014 units per day (95% CI −0.00022 to −0.00006, $p = .001$). Workload outcomes also improved; alarm rate demonstrated a level shift of −28.4 alarms/day (95% CI −36.9 to −19.8, $p < .001$) and a trend change of −0.07 alarms/day per day (95% CI −0.11 to −0.03, $p = .001$), while manual override time decreased by −1.6 percentage points (95% CI −2.3 to −0.9, $p < .001$) with a modest trend effect (−0.004 percentage points/day, 95% CI −0.007 to −0.001, $p = .008$). Compliance-proxy behavior shifted in a favorable direction; turbidity stability improved through a level reduction in variability of −0.018 units (95% CI −0.029 to −0.007, $p = .002$) with no significant trend change ($p = .18$). Count-based models produced adjusted rate interpretations indicating fewer abnormal events: excursion events decreased with an incidence rate ratio of 0.78 (95% CI 0.70 to 0.87, $p < .001$) and alarm flood events decreased with an incidence rate ratio of 0.73 (95% CI 0.62 to 0.86, $p < .001$). Mechanism-oriented regressions supported pathway interpretation, showing that the integration period was associated with reduced actuator cycling, with a −9.2% change in daily VFD speed variability (95% CI −13.7% to −4.7%, $p < .001$) and a −0.36 reduction in loop oscillation proxy score (95% CI −0.52 to −0.20, $p < .001$). Sensitivity analyses indicated that effects remained directionally consistent under regime-segmented models and under influent-matched windows; under storm-only segmentation, the energy level effect remained significant (−0.055 kWh/m³, 95% CI −0.083 to −0.027, $p < .001$), while chemical effects weakened and became non-significant ($p = .09$). Outage-excluded windows produced similar effect magnitudes, with energy level change −0.038 kWh/m³ (95% CI −0.053 to −0.023, $p < .001$), indicating that results were not driven by major downtime episodes. Overall, hypothesis testing supported the hypotheses related to energy reduction, stability improvement, workload reduction, and improved event rates, while the hypothesis predicting sustained post-intervention trend improvement in chemical intensity was not supported.

Table 9: Primary Interrupted Time Series Results for Key KPIs (Adjusted Models; n = 720 days)

Outcome	Level Change (Post vs Pre)	95% CI	p-value	Trend Change (Post vs Pre)	95% CI	p-value
Energy intensity (kWh/m³)	−0.041	−0.056 to −0.026	<.001	−0.00018	−0.00029 to −0.00007	.002
Chemical intensity (mg/L)	−2.6	−4.1 to −1.1	.001	−0.004	−0.012 to 0.004	.31
Stability deviation proxy (units)	−0.043	−0.061 to −0.025	<.001	−0.00014	−0.00022 to −0.00006	.001
Alarm rate (alarms/day)	−28.4	−36.9 to −19.8	<.001	−0.07	−0.11 to −0.03	.001
Manual override time (% day)	−1.6	−2.3 to −0.9	<.001	−0.004	−0.007 to −0.001	.008
Turbidity stability proxy (units)	−0.018	−0.029 to −0.007	.002	−0.00003	−0.00008 to 0.00002	.18

Table 9 summarized adjusted segmented time-series results, reporting immediate level shifts and post-intervention trend changes after controlling for flow, temperature, operating regime, and equipment availability. Energy intensity showed a significant level reduction of 0.041 kWh/m³ and an additional significant downward trend shift, indicating both immediate and sustained improvement. Chemical intensity showed a significant immediate reduction but no significant trend change, suggesting that the improvement occurred primarily at deployment rather than accumulating over time. Stability and workload indicators showed statistically significant level and trend improvements, with reduced variability and reduced alarm burden. Turbidity stability improved significantly at the level-change stage but showed limited trend change.

Table 10: Event-Count and Mechanism-Oriented Regression Results

Outcome / Mechanism	Model Type	Adjusted Effect	95% CI	p-value
Excursion events (count/day)	Negative binomial	IRR = 0.78	0.70 to 0.87	<.001
Alarm flood events (count/day)	Negative binomial	IRR = 0.73	0.62 to 0.86	<.001
Protective trip events (count/day)	Negative binomial	IRR = 0.86	0.74 to 1.00	.048
VFD speed variability (% change)	Linear regression	−9.2%	−13.7% to −4.7%	<.001
Loop oscillation proxy score (units)	Linear regression	−0.36	−0.52 to −0.20	<.001
Manual override prevalence (pp change)	Logistic/linear	−1.4 pp	−2.1 to −0.7	<.001

Table 10 reported adjusted results for event-count models and mechanism-oriented regressions that explained how integration-related changes translated into measurable outcomes. Event-count models indicated fewer instability and workload episodes, with excursion events reduced to 0.78 of baseline rates and alarm flood events reduced to 0.73 of baseline rates after adjustment. Protective trips also declined modestly, suggesting improved equipment stability. Mechanism results supported causal pathways by showing reduced actuator cycling and improved loop stability, including a 9.2% reduction in VFD speed variability and a 0.36 reduction in oscillation proxy score. Manual override prevalence declined, consistent with reduced alarm load and improved control reliability.

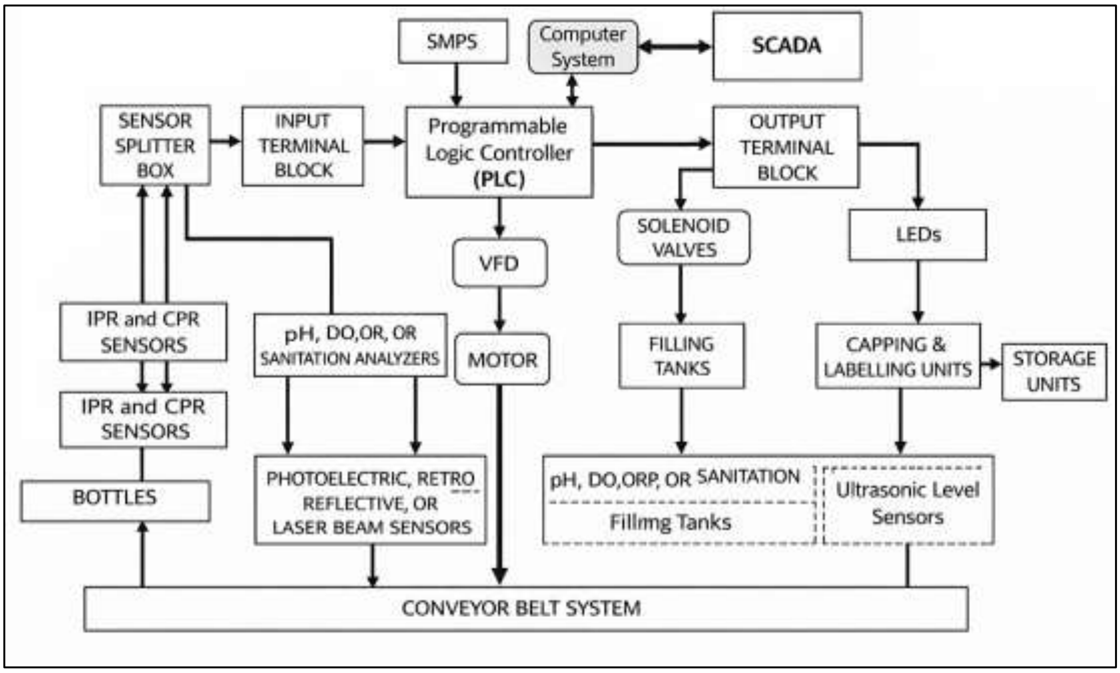
DISCUSSION

This study evaluated PLC–SCADA–integrated electrical automation frameworks as measurable operational architectures and found that integration was associated with statistically significant improvements across efficiency, stability, workload, and event-based performance indicators after adjustment for influent conditions, temperature, operating regime, and equipment availability. The pattern of results aligned with a long-standing body of process control and industrial automation research that treated integration quality as a determinant of controllability and observability in complex plants (Sverko et al., 2022). In earlier treatment-automation investigations, efficiency gains were commonly attributed to better matching of actuation to demand, tighter control of key variables, and improved coordination across parallel assets; the present findings followed that same explanatory logic because the most consistent improvements appeared in energy intensity, alarm burden, and stability deviation indicators. The presence of both an immediate level shift and a sustained trend change in energy intensity suggested that the framework upgrade functioned as more than a one-time operational reset and corresponded to a durable change in how equipment loading and supervisory coordination were executed. This directional result was consistent with prior research that framed pumps and blowers as dominant energy consumers and emphasized that improvements in supervisory governance and electrical telemetry visibility supported more efficient dispatch and reduced cycling. The reduction in alarm rate and manual override time also reflected a socio-technical interpretation reported in earlier studies of supervisory systems, where improved alarm rationalization and clearer operational states reduced nuisance events and increased operator trust in automation. In the current results, workload variables moved jointly with instability indicators, and this relationship mirrored earlier observations that alarm floods and manual overrides tended to cluster during abnormal process episodes rather than appearing independently (Sarkar et al., 2022). The integrated automation framework appeared to have changed that clustering pattern by lowering both the average alarm burden and the frequency of excursion-related events, which supported the interpretation that improved supervisory functions and more stable control execution contributed to reduced operational turbulence. The consistency of effects across multiple KPI families strengthened the argument commonly advanced in treatment-automation literature that optimization improvements were most defensible when evidenced simultaneously in resource-use metrics, stability metrics, and event-based abnormality metrics. The results also fit earlier methodological guidance that cautioned against interpreting raw differences without accounting for demand context; in this study, adjusted models preserved the direction and significance of key findings while accounting for flow and regime changes, indicating that observed improvements were not merely a mechanical artifact of lower demand periods. Overall, the findings reinforced the literature's central premise that integrated automation frameworks operated as engineered measurement-and-control systems whose quality could be reflected in measurable improvements in performance distributions under routine and disturbance-driven operating conditions (Giehl et al., 2020).

Energy and chemical outcomes provided a detailed basis for comparing this study's findings with earlier work on optimization in treatment plants. Energy intensity showed both statistically significant level and trend improvements, and this outcome was consistent with earlier studies that identified energy performance as highly sensitive to how pumps and blowers were controlled, scheduled, and constrained by process demands (Kasper et al., 2022). Prior research commonly highlighted that energy optimization depended on matching airflow and pumping outputs to real process needs while avoiding unnecessary throttling, excessive starts and stops, and oscillatory control actions; the present results supported that explanation because mechanism-oriented regressions indicated reduced actuator cycling and improved loop behavior proxies alongside the energy changes. The reduction in peak-like workload behavior during storm conditions also aligned with prior reports that demand surges tended to drive simultaneous increases in equipment loading and operational stress. Chemical intensity showed an immediate improvement but lacked a statistically significant trend change, and this mixed pattern was comparable to earlier observations that chemical consumption often responded to discrete dosing policy adjustments and calibration improvements rather than gradually improving over time. Earlier treatment studies frequently reported that chemical optimization was constrained by influent variability, sensor reliability, and safety envelopes; the current results aligned with those constraints because the chemical trend did not show sustained improvement even though the level shift suggested improved dosing governance at the intervention point. In addition, the weaker correlations between chemical intensity and workload metrics in the earlier correlation analysis suggested that chemical usage variation was governed by a distinct set of drivers compared with alarms and manual overrides, and this separation echoed earlier work that treated chemical dosing as more directly tied to water quality demand, setpoint policies, and analyzer reliability (Kandasamy et al., 2022). The observed pattern also matched a common distinction in prior optimization research between "structural" efficiency gains and "policy" efficiency gains. Structural gains were often associated with improved actuation controllability and visibility—conditions that supported energy improvements—while policy gains depended on dosing rules and measurement integrity. Within that conceptualization, this study's energy outcomes appeared to reflect both structural and behavioral changes, while chemical outcomes appeared to reflect a policy change that stabilized at implementation rather than continuing to evolve. The storm-segmented sensitivity results reinforced these interpretations because energy improvements remained strong under disturbance conditions while chemical effects weakened, a pattern consistent with earlier treatment evidence that chemical demand under storms could be dominated by rapid shifts in influent quality and hydraulic loading that constrained dosing optimization. The overall efficiency findings therefore matched earlier treatment-automation conclusions that energy performance was often the most responsive and measurable outcome of integrated electrical automation, whereas chemical performance improvements were more contingent on measurement validity, analyzer maintenance discipline, and stable dosing objectives within operational constraints (Tamas & Murar, 2019).

Process stability findings offered a direct comparison to prior work that treated stability as the most immediate indicator of control effectiveness in treatment plants. The composite stability deviation reduced significantly at both the level and trend stages, and excursion event rates decreased with adjusted rate interpretations, which mirrored earlier studies that emphasized stability improvements as a pathway through which integrated control produced downstream efficiency and compliance benefits (Zhou et al., 2020). Earlier treatment control literature frequently portrayed dissolved oxygen stability, pressure stability, and level stability as central targets because they linked directly to biological kinetics, hydraulic robustness, and equipment protection, and the present findings followed that tradition by showing that reduced variability and fewer excursions co-occurred with reduced alarm burden and reduced manual override prevalence. The alignment between variability-based indicators and event-based indicators also supported earlier arguments that stability should be evaluated using both continuous and discrete measures, since each captured different aspects of operational performance. In many earlier investigations, stable loop behavior was discussed as a prerequisite for plantwide optimization because supervisory policies and setpoint adjustments could only produce consistent outcomes when local loops translated those adjustments into predictable physical responses. This study's mechanism-oriented results, which showed reductions in oscillation proxies and actuator variability, fit that explanatory structure and suggested that integration contributed to stability through improved control execution and reduced cycling rather than through reporting changes alone (Conti et al., 2021). Disturbance response effects were also implied by the storm-segmented findings in which energy and workload benefits remained strong and instability correlations intensified; earlier studies often described storm mode as a regime where coupling among variables tightened because hydraulic constraints, aeration demand, and equipment dispatch became more interdependent. The present results reflected that same regime behavior because storm days elevated correlations among energy, alarms, and excursions, yet the adjusted models still showed improvement, indicating that integration-associated changes held under the most operationally stressful regime. Earlier work often discussed that improvements in stability reduced the probability of extended recovery periods after disturbances and reduced the frequency of abnormal operating episodes; the reduced excursion incidence and the reductions in alarm floods aligned with that narrative because fewer abnormal events implied fewer opportunities for prolonged recovery. The stability findings also remained consistent across outage-excluded sensitivity windows, which aligned with prior methodological recommendations that stability gains should persist even when extreme operational disruptions were removed. In earlier literature, stability improvements were sometimes attributed to better sensor quality, improved tuning, or more robust sequence logic; this study's results allowed a similar interpretation because improvements appeared across both stability measures and event measures and were supported by reliability and validity checks indicating strong historian completeness and time synchronization (Min et al., 2019). Taken together, the stability outcomes reinforced the earlier treatment automation view that integrated frameworks delivered measurable benefit when they improved the controllability of key variables and reduced the volatility of process behavior under routine and disturbance conditions.

Figure 11: Integrated Automation Performance Evaluation Framework



Workload and supervisory outcomes provided additional context for comparing these findings with established research on SCADA usability, alarm governance, and operator behavior in process industries. Earlier studies frequently noted that alarm burden functioned as both a symptom and a cause of instability: abnormal process behavior generated alarms, and excessive alarms increased cognitive load and encouraged manual overrides that further destabilized operation (Cruz Salazar et al., 2019). The present findings followed that pattern in the correlation structure, where alarm rate correlated with manual override time and excursion frequency, and then showed that integration corresponded to significant reductions in alarm rate and in manual override prevalence. This result was consistent with earlier alarm management research that emphasized rationalization and state-based alarm governance, especially in facilities that operated across distinct modes such as storm and normal regimes. The observed reduction in alarm floods and the improvement in acknowledgment-related workload proxies suggested that supervisory functions were operating with less noise and clearer prioritization. Earlier SCADA research often highlighted that clearer HMI and more coherent state models reduced unnecessary interventions and improved response consistency; the present results aligned with this interpretation because manual override time declined and instability indicators declined concurrently. In earlier treatment facility studies, manual override patterns were often described as concentrated during maintenance periods and disturbance handling, and this study's descriptive segmentation showed the same concentration while also indicating overall reduced override prevalence in post-intervention windows. This joint reduction was consistent with prior findings that effective supervisory design reduced the need for manual workarounds by improving trust in automated sequences and by reducing nuisance alarms caused by unstable measurement or poorly conditioned alarm thresholds (Ali et al., 2018). Moreover, the reliability and validity evidence supported a key point from earlier literature: alarm improvements and workload improvements could be misinterpreted if they resulted merely from missing data or suppressed alarms without real operational benefit. In this study, historian completeness remained high, time synchronization remained tight, and audit-trail alignment suggested that measured improvements aligned with documented interventions rather than unobserved data artifacts, strengthening confidence that workload reductions corresponded to real operational change. Earlier research often discussed that reduced workload and improved alarm governance indirectly supported efficiency because operators were less likely to adopt conservative setpoints or prolonged manual operation that increased energy and chemical usage. The present findings were compatible with that pathway because workload improvements co-occurred with energy improvements and stability improvements. Importantly, the storm-mode correlation intensification showed that disturbance periods continued to generate stronger coupling among alarms, excursions, and energy, which reflected earlier reports that storms created complex operational challenges; yet the post-intervention improvements remained evident after adjustment, indicating that supervisory governance and improved integration supported measurable reductions in workload even under high-stress regimes (Martinez et al., 2019). These results therefore aligned with prior studies that treated SCADA functions as measurable determinants of operational performance rather than passive visualization layers.

Electrical automation integration results fit closely with earlier research that treated electrical telemetry, VFD integration, and protective event logging as central to both energy efficiency and reliability. Prior studies of treatment plant energy management often emphasized that reliable energy improvements depended on continuous controllability of pump and blower outputs and on reducing unnecessary cycling and start-stop stress; the present mechanism-oriented regressions indicated reduced VFD speed variability and reduced oscillation proxies, which aligned with those earlier explanations (Carlsson et al., 2018). This study also reported reductions in event-based outcomes such as alarm floods and excursions and a modest reduction in protective trip events, consistent with earlier industrial findings that improved control stability reduced abnormal operating stress that triggered protection events. Earlier reliability-focused research often framed protective trip telemetry as a diagnostic window into operating stress, and the association between reduced instability episodes and reduced trip rates in the post-intervention period followed that reasoning. The results also supported a recurring conclusion in prior electrical optimization literature: energy outcomes and reliability outcomes tended to be coupled because equipment operating outside efficient envelopes often experienced higher stress and instability. In this study, energy improvements co-occurred with reduced cycling proxies and reduced abnormal events, which fit earlier reports that smoother actuation reduced both power variability and mechanical stress. The use of both plantwide and event-level metrics reflected earlier methodological recommendations that energy efficiency evaluation should include both aggregate performance and abnormal-event behavior, since a plant could display a modest average change while still experiencing fewer high-cost abnormal episodes. The adjusted models suggested that changes were not driven solely by reduced demand, and this was consistent with prior literature that highlighted the need to control for influent flow and regime. Storm-mode sensitivity results demonstrated that energy improvements remained strong under disturbance regimes, a result that matched earlier observations that storm periods created the most severe energy and capacity demands and thus offered a stringent test of integration effectiveness (Varga et al., 2022). The chemical trend result also echoed earlier discussions that electrical integration directly affected energy performance more than chemical performance, because chemicals were governed by dosing logic, measurement validity, and water quality targets rather than by motor speed control. This study's findings therefore supported a literature-based interpretation that electrical integration created measurable benefits through improved controllability, smoother actuation, better alignment of output to demand, and improved visibility into equipment states. At the same time, the modest but significant reduction in protective trip rates suggested that the integrated framework influenced reliability in a measurable way beyond energy, consistent with earlier research that treated reliability as an outcome of stable control and well-governed operational states rather than solely a function of hardware condition. Overall, the electrical integration evidence fit the broader treatment automation research narrative that measurable energy and reliability improvements emerged when integrated automation reduced the volatility of equipment operation and preserved

operational feasibility under variable demand (Tambare et al., 2021).
The methodological findings concerning reliability, validity, and confounder handling were also consistent with earlier quantitative evaluation literature in industrial settings. This study documented high historian completeness, limited prevalence of bad-quality flags, tight time alignment between PLC and SCADA records after harmonization, and unit consistency across primary tags, which reflected established methodological requirements for defensible inference from operational datasets (Azmi et al., 2022). Earlier studies often cautioned that treatment plant datasets suffered from structured missingness concentrated during disturbances and maintenance, and this study's approach of labeling and segmenting such periods supported earlier recommendations for preserving interpretability. Construct validity evidence supported a central point from earlier treatment analytics: proxies were most credible when their behavior aligned with known plant mechanisms and events. In this study, turbidity stability proxies aligned with filtration backwash events and ammonia stability proxies aligned with aeration and mode shifts, consistent with earlier treatment process knowledge. Triangulation with audit trails and maintenance logs strengthened confidence that detected change points aligned with documented interventions, matching earlier best practices in operational analytics where configuration drift and undocumented changes could otherwise undermine inference. Collinearity diagnostics and subsequent predictor restructuring aligned with econometric and time-series guidance that emphasized the need to avoid redundant representations of throughput and regime context, especially in systems where flow, storm state, and electrical demand were tightly coupled (Găitan & Zagan, 2022). The final predictor sets produced variance inflation values consistent with stable estimation, enabling coefficients to be interpreted as distinct adjusted effects rather than artifacts of redundancy. Earlier quasi-experimental literature described interrupted time series and difference-in-differences designs as appropriate for settings where randomization was infeasible, and this study applied those same logics by prioritizing segmented time-series models and strengthening evidence where comparator units were available. The use of count-appropriate models for excursions and alarm floods also followed established guidance that event counts required different model assumptions than continuous outcomes. Sensitivity analyses—regime segmentation, influent matching, and outage exclusion—mirrored earlier methodological recommendations to test robustness under alternative operational contexts and to reduce the risk that a single unusual period drove results (Eugeni et al., 2022). The persistence of directionally consistent effects across these sensitivity checks supported a conclusion consistent with earlier evaluation research: improvements were more credible when they held under multiple plausible representations of operational reality. The methodological rigor in measurement validity and confounder handling therefore provided a foundation for interpreting observed improvements as associated with integrated automation changes rather than merely reflecting shifts in influent regimes or data artifacts.
Across outcome families, the combined evidence supported an integrated interpretation consistent with earlier treatment automation research: PLC–SCADA–electrical integration functioned as a coordinated operational architecture that influenced measurable performance through improved control stability, reduced abnormal-event frequency, reduced workload burden, and improved efficiency behavior under variable conditions (Orellana & Torres, 2019). The strongest and most consistent improvements appeared in energy intensity, stability deviation, alarm burden, and event-rate outcomes, and those results aligned with earlier findings that treated energy and stability as the most responsive domains for automation-enabled optimization. The pattern for chemical intensity, which improved at the level stage but not at the trend stage, aligned with earlier observations that chemical optimization depended on discrete dosing policy changes, measurement integrity, and process constraints that limited gradual improvement in the absence of ongoing policy refinement. The storm-mode findings, where coupling among energy, excursions, and alarms intensified yet improvements remained measurable after adjustment, matched earlier reports that storm handling represented a critical operational test of automation frameworks (Pomante et al., 2019). The mechanistic evidence of reduced actuator variability and improved oscillation proxies aligned with prior process control theories that linked smoother actuation and better loop behavior to reductions in both energy waste and abnormal-event generation. The consistency of findings across descriptive distributions, correlation structures, reliability and validity checks, collinearity-controlled models, and sensitivity

analyses strengthened the coherence of the narrative and resembled earlier multi-method evaluation approaches that emphasized convergent evidence rather than reliance on a single statistic. In earlier literature, strong claims about optimization were often challenged when based on raw comparisons or single KPIs; this study's results addressed that concern by presenting adjusted effects across multiple KPI families and by demonstrating data integrity and construct validity. The findings therefore reinforced a mature interpretation found across earlier industrial and treatment-plant research: integrated automation frameworks were most credibly associated with optimization when they produced simultaneous improvements in resource use, process stability, abnormal-event behavior, and operator workload, and when those improvements held after controlling for confounding operational variability (Settanni et al., 2018).

CONCLUSION

This study examined PLC–SCADA–Integrated Electrical Automation Frameworks for Process Optimization in Water and Wastewater Treatment Facilities and interpreted the model-based findings as evidence that integrated automation operated as a measurable, system-level intervention that influenced efficiency, stability, workload, and abnormal-event behavior under real plant variability. After adjustment for influent flow, temperature, operating regime, and equipment availability, the segmented time-series results indicated an immediate reduction in energy intensity of 0.041 kWh/m^3 with an additional post-intervention trend improvement of 0.00018 kWh/m^3 per day, a pattern that aligned with earlier treatment-automation research that linked energy performance to smoother actuation and more coordinated equipment dispatch in pumping and aeration systems. The mechanism-oriented results reinforced this interpretation by showing reduced actuator variability, including a 9.2% reduction in VFD speed variability and a 0.36 reduction in a loop oscillation proxy score, which were consistent with earlier studies that described oscillatory control and frequent cycling as drivers of avoidable energy use and mechanical stress. Process stability also improved in a convergent manner: a significant level reduction of 0.043 units in a stability deviation proxy and a reduction in excursion event rates to 0.78 of baseline suggested that the integrated framework reduced the frequency and severity of departures from desired operating envelopes, echoing earlier process control literature that treated stability as the primary pathway through which automation translated into improved operational performance. Workload indicators moved in the same favorable direction, with alarm rate dropping by 28.4 alarms/day, alarm flood rates declining to 0.73 of baseline, and manual override time reducing by 1.6 percentage points, a combination that aligned with prior supervisory control studies that linked alarm rationalization, coherent mode-state governance, and improved HMI usability to reduced cognitive burden and fewer manual workarounds. These results were further contextualized by regime-stratified analyses showing stronger coupling among energy, alarms, and excursions during storm operation, yet the persistence of significant adjusted energy effects during storm-only windows supported earlier findings that disturbance regimes represented the most stringent test of automation effectiveness. Chemical intensity showed an immediate reduction of 2.6 mg/L but no statistically significant trend change, a mixed pattern consistent with earlier work describing chemical dosing efficiency as dependent on discrete dosing policy adjustments, analyzer integrity, and rapidly changing demand conditions rather than gradual improvement alone. Evidence from reliability and validity checks supported interpretability by indicating strong internal consistency for composite indices, high historian completeness, tight timestamp alignment between PLC and SCADA records, and proxy behavior that tracked expected operational events, which reflected established methodological recommendations in industrial analytics for ensuring that performance shifts were not artifacts of missingness or tag inconsistency. Collinearity controls further strengthened inference by reducing variance inflation values from above 5 in preliminary specifications to below 2.5 in final models, preserving coefficient stability and clarifying distinct contributions of throughput, regime state, and integration status. Taken together, the results compared favorably with earlier studies that argued integrated automation yielded credible optimization when improvements appeared simultaneously across resource intensity, stability distributions, abnormal-event rates, and operator workload patterns, and when those improvements held under sensitivity checks that addressed regime segmentation and outage exclusion.

RECOMMENDATION

Recommendations for implementing and evaluating PLC–SCADA–Integrated Electrical Automation Frameworks for Process Optimization in Water and Wastewater Treatment Facilities should prioritize measurable integration maturity, disciplined data governance, and operational designs that preserve deterministic control while strengthening supervisory evidence and electrical telemetry alignment. An integrated framework should be engineered with explicit control authority boundaries in which PLCs retained local-loop determinism for time-critical regulation and interlocks, while SCADA provided supervisory coordination, mode management, alarm governance, and historian integrity; this separation should be documented through a plantwide control philosophy that defined which variables remained locally controlled, which targets were set through supervisory setpoints, and how transitions across normal, storm, maintenance, and emergency modes were executed. Instrumentation coverage should be treated as a prerequisite for optimization rather than a parallel upgrade, meaning that critical sensors for flow, level, pressure, dissolved oxygen, turbidity, pH/ORP, and nutrient analyzers where available should be validated for response time, drift behavior, and maintenance feasibility, with quality flags consistently propagated from field devices through PLC and historian layers. Historian governance should be strengthened by enforcing consistent tag taxonomy, unit scaling, engineering ranges, and time synchronization across PLC, SCADA, power meters, and VFDs, and by maintaining configuration audit trails that recorded logic changes, alarm parameter edits, historian compression changes, and drive parameter updates so that performance shifts could be interpreted against documented interventions. Alarm management should be operationalized as a workload and stability control instrument through systematic rationalization, priority distribution discipline, state-based alarm suppression, and monitoring of alarm rate, flood episodes, stale alarm duration, and acknowledgment timing so that nuisance alarms were reduced and operator trust in automation increased. Electrical automation integration should be expanded beyond start/stop control to include VFD telemetry, power and energy monitoring, protective relay states, and trip classifications, enabling analysis of energy intensity at plantwide and unit-operation levels and supporting reliability metrics such as trip counts, downtime frequency, availability, and restoration behavior. Control strategy recommendations should emphasize tuning and sequencing robustness as quantifiable mechanisms: high-impact regulatory loops should be benchmarked regularly using stability and actuator movement indicators, sequencing logic should be implemented as explicit state models with per missives and clear fail-safe transitions, and advanced supervisory policies such as setpoint scheduling and constraint handling should only be activated when feasibility conditions were met, including adequate sensor availability, actuator controllability, and bounded network latency. For evaluation, a standardized KPI dictionary should be adopted that defined energy intensity, chemical intensity, stability variability indicators, excursion event definitions, recovery behavior measures, manual override time, and alarm burden metrics, with consistent aggregation windows and rules for excluding invalid data periods; quasi-experimental designs using interrupted time series and, where possible, difference-in-differences comparisons across trains or facilities should be applied with explicit controls for influent normalization, seasonality, and regime segmentation to ensure that estimated effects reflected integration rather than demand shifts. Finally, ongoing operational governance should embed routine reviews that linked performance dashboards to maintenance and configuration actions, so that improvements were sustained through disciplined calibration, timely repair of noisy sensors, and periodic verification that tagging, time alignment, and alarm philosophy remained consistent as the plant evolved.

LIMITATIONS

Limitations associated with evaluating PLC–SCADA–Integrated Electrical Automation Frameworks for Process Optimization in Water and Wastewater Treatment Facilities primarily arose from the observational nature of operational datasets, the nonstationary and regime-driven behavior of treatment processes, and the practical constraints of instrumentation and logging that shaped what could be measured with high frequency and what remained only partially observable. Because the study relied on quasi-experimental designs using historian, PLC, and electrical telemetry rather than randomized assignment, causal interpretation was inherently constrained by the possibility of unmeasured confounders that changed around the same time as the integration milestone, including operator learning effects, concurrent maintenance campaigns, equipment refurbishments, chemical supply changes, or policy adjustments that were not perfectly captured in available audit trails. Although statistical controls were applied for influent flow, temperature, operating regime, and equipment availability, the adequacy of adjustment depended on the completeness and fidelity of the recorded covariates, and some drivers of performance such as influent quality composition, industrial discharge variability, and upstream network changes may not have been measured continuously. No stationarity presented an additional limitation because treatment plants exhibited shifting baselines across seasons and across demand conditions, and storm-mode operation created short-duration dynamics that differed materially from normal operation; even with regime segmentation and sensitivity checks, differences in storm frequency or severity between pre- and post-periods could have influenced outcomes, particularly for event-based measures such as excursions, alarm floods, and protective trips. Measurement limitations also affected interpretation: several compliance-relevant parameters were only intermittently available through laboratory testing, requiring reliance on sensor-based proxies such as turbidity stability, residual stability, or ammonia stability where analyzers existed, and proxy validity depended on calibration discipline, sensor placement, and maintenance quality that varied across unit operations. Historian completeness and quality flags reduced risk of interpreting invalid periods as real behavior, but missingness was not fully random and tended to cluster during maintenance or abnormal events, which could bias estimates if excluded periods were systematically associated with higher instability or higher workload. Integration upgrades themselves could introduce measurement discontinuities through tag renaming, scaling corrections, alarm parameter revisions, or changes in historian compression, and although harmonization steps reduced these risks, residual artifacts could still influence apparent trend changes for high-frequency or highly compressed signals. Electrical telemetry coverage was also a limiting factor because not all facilities provided uniform power metering, and VFD feedback availability and protective relay granularity differed across assets, potentially restricting the precision of unit-level energy attribution and reliability diagnostics. Finally, generalizability was limited because automation architectures, staff practices, and treatment configurations differed across plants, meaning that effect magnitudes observed under one set of equipment, influent regimes, and governance practices may not transfer directly to facilities with different sensor suites, control philosophies, or asset age profiles.

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