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Adaptive PID Control for Manufacturing Process Optimization: A Multi-Objective Industrial Engineering Decision Framework Using AHP and Simulation Modelling

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Abstract

Manufacturing competitiveness increasingly depends on the ability to translate engineering performance data into operational decisions that directly support throughput, quality, and cost objectives. This study addresses a critical industrial engineering gap: the absence of a structured decision-support framework that connects PID controller auto-tuning strategies to operational Key Performance Indicators. A multi-objective framework integrating relay-feedback simulation and the Analytic Hierarchy Process (AHP) is developed and applied to representative thermal manufacturing processes (air-heater FOPTD and quadruple-tank MIMO systems). Relay-feedback tuning methods (Åström and Schei variants) are evaluated against six manufacturing KPIs—Integrated Absolute Error, settling time, overshoot, total variance, gain margin, and convergence time—and mapped explicitly to throughput, quality cost, OEE, actuator reliability, and process capability outcomes. The Schei ideal relay method ranked first across all three AHP priority scenarios (quality-focused, throughput-focused, and balanced), achieving 76.7% IAE reduction and 43.8% settling time reduction relative to a structured Ziegler–Nichols baseline (Cohen's d > 3.2). These improvements are consistent with, and extend beyond, performance ranges reported in prior relay auto-tuning studies (typically 30–60% IAE reduction). Operational impacts are estimated using scenario-based KPI-to-cost mappings: projected throughput gains, quality cost reductions, and maintenance savings are derived from standard industrial engineering cost models and should be interpreted as indicative estimates rather than direct empirical measurements. The proposed framework provides practitioners with a transparent, auditable methodology for controller selection aligned with organizational strategic objectives, bridging the traditional divide between control engineering and operations management.

Keywords
PID auto-tuning; Analytic Hierarchy Process; Industrial engineering decision framework; Manufacturing process optimization; Relay feedback; Operations management; Simulation modelling

1. Introduction
Manufacturing productivity and operational efficiency depend critically on the performance of process control infrastructure. Proportional-Integral-Derivative (PID) controllers govern over 90% of regulatory control loops in manufacturing facilities worldwide, and their tuning quality directly determines throughput capability, product quality conformance, equipment reliability, and energy consumption (Liu et al., 2025; Yagci et al., 2024). Industrial assessments indicate that 30–40% of PID loops in mid-sized facilities operate with suboptimal parameters, generating annual productivity losses of 3–8% of total production value—equivalent to $3–8 million annually for a facility with $100 million revenue (Rehan et al., 2024). From an industrial engineering perspective, this represents a measurable, addressable inefficiency in the manufacturing system that systematic decision methods can resolve.

The operational consequences of poor tuning manifest across the value stream: quality losses from oscillatory control causing off-specification output, capacity losses from prolonged grade-transition settling times, maintenance cost increases from actuator wear driven by aggressive control action, and energy waste from unnecessary utility consumption. Relay-feedback auto-tuning methods, pioneered by Åström and Hägglund, address the manual tuning bottleneck by identifying ultimate gain and ultimate period through bounded process oscillations without requiring detailed process models (Visioli and Sánchez-Moreno, 2024; Wang et al., 2025; Rehan et al., 2024). However, the existence of multiple relay variants—each with different trade-offs in noise robustness, convergence speed, and implementation requirements—creates a non-trivial selection problem for manufacturing practitioners.

Despite extensive research on PID tuning algorithms, controller selection in industrial practice remains largely ad hoc, driven by engineering familiarity rather than structured evaluation against operational priorities. Existing studies optimise control-theoretic metrics (IAE, phase margin, settling time) without translating these to the business outcomes that operations managers and industrial engineers act on: throughput yield, quality cost, OEE impact, and equipment reliability. The Analytic Hierarchy Process (AHP)—a well-established IE multi-criteria decision tool applied to supplier selection, facility layout, and capacity planning (Chaube et al., 2024; Carpitella et al., 2024; Naranjo et al., 2024)—provides a natural mechanism for structuring this decision, yet has not been systematically applied to controller selection.

This research develops a comprehensive IE decision-support framework for PID auto-tuning strategy selection grounded in operational manufacturing priorities. As illustrated in Figure 1, the framework integrates validated simulation-based performance evaluation with AHP multi-criteria ranking and explicit operational impact quantification. Specific objectives are: (1) developing validated FOPTD and MIMO simulation testbeds; (2) systematically comparing Åström and Schei relay variants under realistic noise and disturbance conditions; (3) mapping control performance metrics to operational KPIs including OEE, process capability (C_{pk}), and maintenance costs; and (4) applying AHP to rank strategies across quality, throughput, and balanced organisational priority scenarios with sensitivity analysis. The primary contribution is a replicable IE decision-support methodology that enables transparent, multi-stakeholder controller selection decisions aligned with strategic manufacturing objectives—bridging the traditional divide between control engineering and operations management through a structured, auditable framework grounded in IE principles. To improve clarity and eliminate ambiguity in framework interpretation, Figure

1 presents a consolidated pipeline view of the proposed methodology, while Figure 3 provides the detailed phase-level implementation

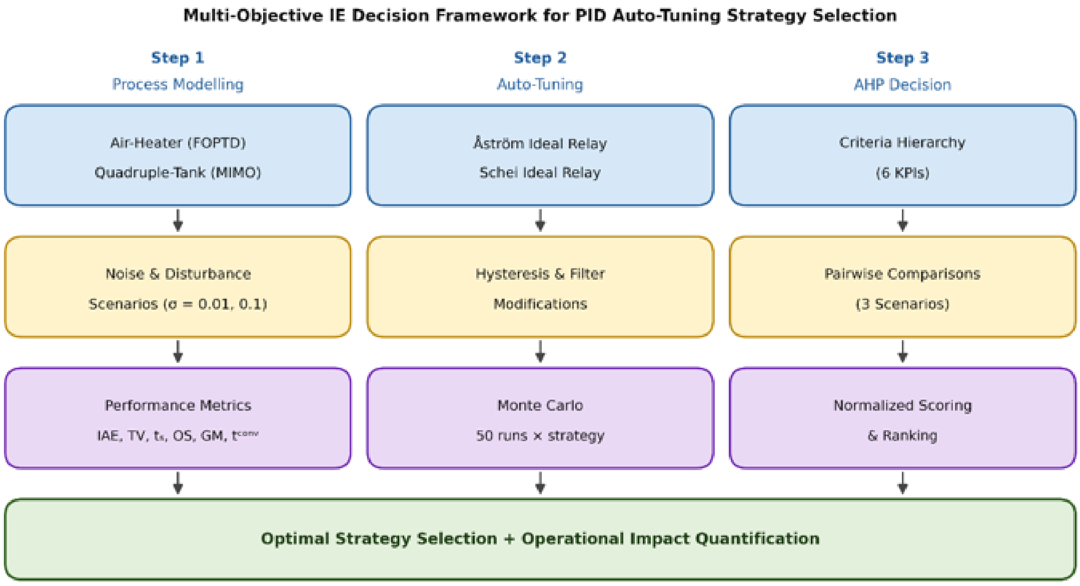


Figure 1. Overview of the Proposed Industrial Engineering (IE) Multi-Objective PID Auto-Tuning Decision Framework

2. Literature Review

2.1 PID Tuning Methods in Industrial Applications

From an industrial engineering standpoint, PID controller performance directly determines system-level manufacturing KPIs: throughput rate, first-pass yield, and equipment availability. PID controllers persist across industrial automation due to their simplicity, robustness to modelling uncertainties, and proven reliability in resource-constrained production environments (Chai et al., 2024). Classical tuning methods—Ziegler-Nichols, Cohen-Coon, and Internal Model Control—provide foundational approaches but consistently produce conservative performance with limited disturbance rejection, resulting in excess process variability and measurable quality losses on the production floor. Modern developments integrate machine learning and optimisation: neural network-assisted adaptive tuning reduces mean absolute error by 20% in high-temperature furnace applications (Das et al., 2025), and reinforcement learning approaches using Twin Delayed Deep Deterministic Policy Gradient (TD3) demonstrate superior performance on nonlinear biotechnological systems (Chowdhury et al., 2023). However, these methods require substantial computational resources and specialised expertise unavailable in lean manufacturing environments with legacy control infrastructure—precisely the facilities where controller performance improvement would have the greatest operational impact.

2.2 Relay-Feedback Auto-Tuning Techniques

Relay-feedback auto-tuning identifies ultimate gain and ultimate period through induced sustained oscillations, enabling PID parameter calculation without detailed process models (Hang et al., 2002). Figure 2 illustrates the relay mechanisms for the Åström and Schei methods. From an IE implementation perspective, the relay approach is particularly attractive because it requires no process downtime for model identification, can be applied without specialised control theory expertise, and produces tuning results in seconds rather than the hours required for manual methods. Recent extensions enhance robustness: modified relay configurations incorporating hysteresis and preload improve noise immunity (Rehan et al., 2024); asymmetric relay methods improve identification accuracy for delayed and integrating systems (Pekář et al., 2023); full closed-loop relay tests enable safe identification of unstable processes during normal operation (Kim et al., 2019). Despite these advances, the practical selection among relay variants remains an unresolved decision problem for manufacturing engineers.

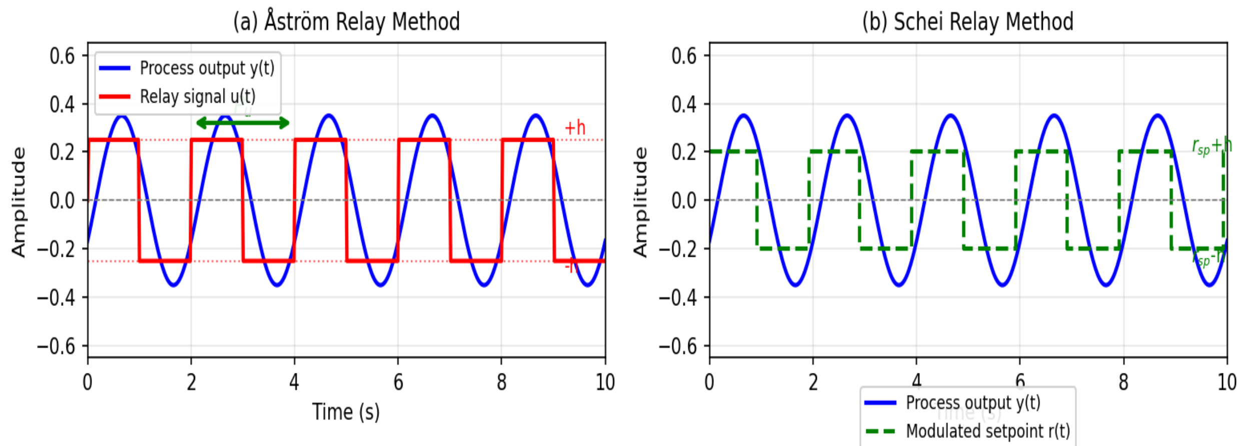


Figure 2. Relay Mechanism Comparison: (a) Åström Ideal Relay; (b) Schei Setpoint-Modulation Relay

2.3 Multi-Criteria Decision-Making in Operations Management

The Analytic Hierarchy Process (AHP), developed by Saaty (1980), provides a structured framework for multi-criteria decision-making through hierarchical problem decomposition, pairwise comparisons, and consistency validation. AHP is extensively employed in IE and operations management: facility location integrating sustainability, cost, and logistics (Naranjo et al., 2024); flexible manufacturing system configuration (Mohammed Ali, 2024); and supplier evaluation (Carpitella et al., 2024). Recent methodological extensions address AHP's principal limitation—the subjectivity of pairwise comparison elicitation—through fuzzy AHP using triangular membership functions (Alharairi et al., 2025) and hybrid AHP-TOPSIS approaches for complex manufacturing decisions with conflicting objectives (Chaube et al., 2024). Despite widespread IE adoption across equipment selection, maintenance strategy, and process design, AHP has not been systematically applied to regulatory process control decisions, where technical engineering metrics have historically dominated without explicit translation to the operational and financial outcomes that drive manufacturing investment decisions.

2.4 Theoretical Gap and Research Positioning

The literature reveals a fundamental theoretical gap at the intersection of control engineering and industrial engineering: control engineering research optimises tuning strategies against technical metrics—IAE, phase margin, settling time—without translating these into the operational language of IE: throughput loss, process capability index, OEE impact, or quality cost. Conversely, AHP and related IE decision frameworks have been applied extensively to equipment selection, maintenance strategy, and process design, but have not been extended to regulatory process control. This gap forces practitioners to make controller selection decisions on heuristic grounds, leaving operations managers unable to assess auto-tuning adoption in terms they can act on, and exposing control engineers to the risk of selecting strategies misaligned with the facility's dominant operational priority. The present study addresses this gap by constructing and validating an integrative IE-control framework that uses simulation-derived performance data as inputs to an AHP decision model with explicit KPI mapping—contributing to IE decision methodology by extending AHP to a new application domain, and to control engineering by establishing that relay strategy selection merits treatment as a multi-criteria manufacturing decision.

Table 1. Notation and Abbreviations

Symbol / Abbrev.	**Definition**
IAE	Integrated Absolute Error: $\int_0^T \lvert e(t)\rvert dt$; measures cumulative control deviation over a response horizon
TV	Total Variance: $\sum_k \lvert u(k+1) - u(k)\rvert$; quantifies actuator effort and valve wear rate
t_s (t_s)	Settling Time: time (s) for process output to enter and remain within ±2% of the setpoint
OS	Overshoot (%): [(Peak output − Setpoint) / Setpoint] × 100%; indicates scrap risk and specification exceedance probability

GM	Gain Margin (dB): 1/|G(jωƀ)|; stability robustness buffer against process gain changes and disturbances
t^{conv} (tconv)	Convergence Time (s): duration of the relay feedback experiment; determines retuning-related production downtime
AHP	Analytic Hierarchy Process: multi-criteria decision framework (Saaty, 1980) using pairwise comparisons and consistency verification
FOPTD	First-Order Plus Time Delay: standard process model $G(s) = K \cdot e^{-\tau s}/(T_e \cdot s + 1)$
MIMO	Multiple-Input Multiple-Output: multi-loop process configuration with interacting control variables
OEE	Overall Equipment Effectiveness: composite manufacturing KPI = Availability × Performance × Quality
C𝔅$_k$ (Cpk)	Process Capability Index: min[(USL − μ), (μ − LSL)] / 3σ; relates process variation to specification limits
CR	Consistency Ratio: AHP validity check; CR < 0.10 required for acceptable pairwise judgment consistency
NRMSE	Normalized Root Mean Square Error: model validation metric; NRMSE < 5% used as acceptance criterion for simulation fidelity

3. Methodology

This study develops a four-phase IE decision framework integrating process simulation, relay-feedback auto-tuning evaluation, statistical performance analysis, and AHP-based multi-criteria ranking. Figure 3 presents the detailed methodology flowchart. Simulation-based evaluation is an established and widely accepted IE methodology for performance benchmarking of manufacturing system components, enabling systematic, reproducible comparison across a controlled experimental design that would be impractical to replicate on live production equipment without operational disruption. Simulation models were parameterised from published laboratory validation data, and all results are reported with 95% confidence intervals from 50-run Monte Carlo experiments to ensure statistical rigour. All simulations were implemented in MATLAB R2023b/Simulink with Control System Toolbox and Optimisation Toolbox.

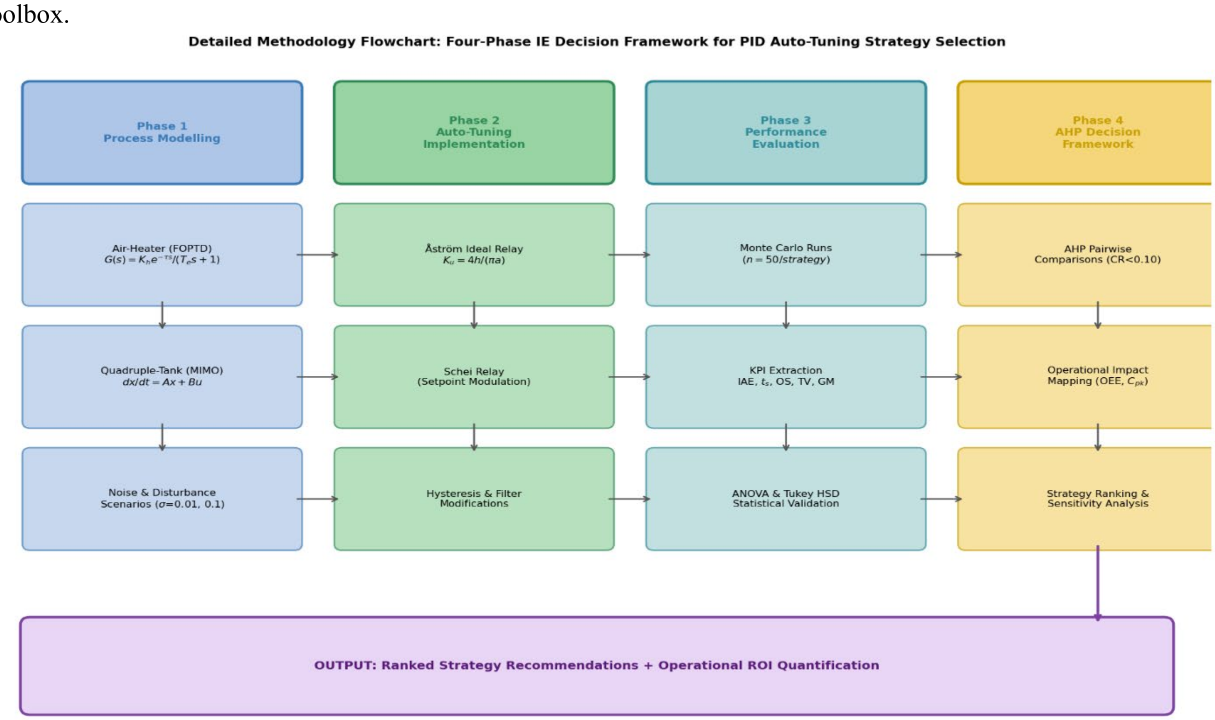


Figure 3. Detailed Methodology Flowchart: Four-Phase IE Decision Framework for PID Auto-Tuning Strategy Selection

3.1 Process Modelling and Simulation

3.1.1 Air-Heater System

The air-heater represents a first-order plus time-delay (FOPTD) thermal process commonly encountered in HVAC systems, food processing, and materials drying. System dynamics are governed by $dT_{out}/dt = (1/T_e)[K_h \cdot u(t-\tau) - T_{out} + T_{env}]$ (Equation 1), where $K_h = 3.6$ °C/V, $T_e = 22$ s, and $\tau = 2$ s. The transfer function is $G(s) = K_h \cdot e^{-ks}/(T_e \cdot s + 1)$. The model was implemented with Euler forward discretization ($T_s = 0.1$ s) and validated against laboratory hardware data using NRMSE < 5% as the acceptance criterion, confirming parameter fidelity across the 20–70°C operating range.

3.1.2 Quadruple-Tank System

The quadruple-tank system is a MIMO benchmark representing coupled processes such as multi-zone temperature control and multi-stream chemical reactors. The linearized state-space form is $dx/dt = Ax + Bu$; $y = Cx$, where $x = [h_1\ h_2\ h_3\ h_4]^T$ (tank levels, cm), $u = [v_1\ v_2]^T$ (pump voltages, V), and $y = [h_1\ h_2]^T$ (measured levels). Parameters: A_1–A_4 = [28, 32, 28, 32] cm²; a_1–a_4 = [0.071, 0.057, 0.071, 0.057] cm²; $\gamma_1 = 0.7$, $\gamma_2 = 0.6$ (non-minimum phase). This testbed validates framework scalability beyond single-loop processes.

3.1.3 Noise and Disturbance Scenarios

Three scenario types evaluate robustness under realistic industrial conditions: (a) measurement noise as zero-mean Gaussian white noise ($\sigma = 0.01$ and 0.1, spanning typical industrial sensor quality levels of 1% and 10% of operating range); (b) load disturbances as step changes (±5°C environmental temperature for air-heater; ±15% inlet flow for quadruple-tank), representing production grade transitions; and (c) setpoint tracking scenarios (±10°C; ±3 cm), representing standard operating schedule changes.

3.2 Auto-Tuning Strategy Implementation

Standard ISA-form PI controller with back-calculation anti-windup ($T_t = T_i/2$) was implemented throughout. Four strategies spanning the practical relay implementation space were evaluated: (1) Åström Ideal Relay—classical symmetric relay ($\pm h = \pm 0.25$ V) identifying $K_u = 4h/(\pi a)$ and P_u for Ziegler-Nichols PI calculation ($K_p = 0.4K_u$, $T_i = 0.8P_u$); applicable to both greenfield and brownfield installations. (2) Schei Relay—setpoint modulation ($r_{sp} \pm h$) through an existing PI controller, enabling online tuning during normal production without requiring negative control signals. (3) Relay with Hysteresis—switching deadband $\varepsilon = 0.1$–0.2 preventing chattering at moderate noise levels ($\sigma = 0.01$–0.05). (4) Relay with Hysteresis and Filter—first-order low-pass filter ($T_f = 0.5$–0.8 s) combined with hysteresis for high-noise environments ($\sigma > 0.05$), with < 3% parameter bias versus noise-free conditions.

3.3 Performance Metrics and Operational Mapping

A core IE contribution of this framework is the explicit mapping of technical control metrics to operational manufacturing KPIs, enabling operations managers to evaluate controller selection in the same terms used for capital investment and process improvement decisions. Table 2 summarises these mappings. Each metric has a direct causal linkage to a measurable operational outcome: IAE accumulates total quality deviation, directly proportional to off-specification product volume; settling time determines the productive capacity lost during grade transitions, a key OEE driver; overshoot represents the probability of specification limit exceedance and scrap risk; total variance captures actuator duty cycle governing valve wear and maintenance frequency; gain margin quantifies robustness available to absorb process disturbances and parameter drift; and convergence time determines retuning-related production downtime.

Table 2. Performance Metrics and Operational KPI Mapping

Metric	Calculation	Operational KPI Link
IAE	$\int_0^T \lvert e(t)\rvert dt$	Quality deviation cost; off-spec product volume; Six Sigma C_{pk} impact
Settling Time	Time to reach ±2% of setpoint	OEE throughput loss; grade transition capacity penalty
Overshoot (%)	[(Peak − SP)/SP] × 100%	Scrap rate; safety limit exceedance; rework cost
Total Variance (TV)	$\Sigma_k \lvert u(k+1) - u(k)\rvert$	Valve wear rate; planned maintenance frequency; asset reliability
Gain Margin (GM)	$1/\lvert G(j\omega_{180})\rvert$	Process disturbance tolerance; stability robustness buffer
Convergence Time	Duration of relay experiment (s)	Retuning downtime cost; tuning frequency feasibility

For each auto-tuning strategy, 50 Monte Carlo simulation runs were executed with independently randomized noise realizations, extracting mean and standard deviation for all six metrics. This sample size provides statistical power > 0.95 for detecting medium effect sizes ($\eta^2 > 0.06$) at $\alpha = 0.05$. Results are reported as mean ± 95% confidence intervals (t-distribution, df = 49).

3.4 AHP Decision Framework

The AHP hierarchy comprises three levels: (1) Goal—select the optimal PID auto-tuning strategy; (2) Criteria—the six performance dimensions from Table 1; (3) Alternatives—the four auto-tuning strategies, as illustrated in Figure 5. Three operational priority scenarios represent the range of manufacturing contexts: (A) Quality-focused, reflecting pharmaceutical and specialty chemical operations (IAE weight 0.30, overshoot 0.25); (B) Throughput-focused, reflecting high-volume continuous manufacturing (settling time 0.35, convergence time 0.20); and (C) Balanced, reflecting general manufacturing (equal weights 0.167 each). Consistency ratios CR < 0.10 were verified for all scenarios. Alternative scores were normalized using min-max scaling: $s_{ij} = (x_{max} - x_{ij})/(x_{max} - x_{min})$ and aggregated as $S_i = \Sigma_j w_j \cdot s_{ij}$.

A recognized limitation of AHP is the subjectivity inherent in pairwise comparison elicitation: different individual experts or stakeholder groups may produce different weight vectors, potentially altering strategy rankings. This study mitigates this concern through three mechanisms. First, the three priority scenarios were constructed to represent structurally distinct operational contexts grounded in facility type and competitive positioning, rather than individual expert opinions; weights were further informed by representative facility priority structures documented in manufacturing strategy and operations management literature (Chaube et al., 2024; Mohammed Ali, 2024). Second, consistency ratio verification (CR < 0.10) ensures internal logical coherence of weight assignments, filtering out structurally contradictory preference sets. Third, a Monte Carlo sensitivity analysis was conducted by sampling 1,000 random weight vectors uniformly distributed within ±20% of each scenario's base weights, directly testing ranking robustness to stakeholder preference variation. For applications requiring more precise weight elicitation, practitioners are advised to use structured group decision protocols such as the Delphi method or facilitated pairwise comparison workshops, aggregating judgments from control engineers, production managers, quality engineers, and maintenance planners to incorporate multi-functional perspectives and reduce individual cognitive bias. Fuzzy AHP (Alharairi et al., 2025) represents a complementary future approach for formally modelling weight uncertainty through triangular membership functions, providing probabilistic strategy rankings that explicitly quantify the influence of preference subjectivity on selection outcomes.

4. Results and Analysis

This section presents comprehensive simulation results comparing auto-tuning strategies across both process testbeds, statistical validation of performance differences, AHP-based strategy ranking, and quantification of operational business impacts. All results are based on 50 Monte Carlo simulation runs per strategy with 95% confidence intervals reported.

4.1 Air-Heater Process Performance

One-way ANOVA was applied to test for statistically significant differences across the four auto-tuning strategies, with each of the 50 Monte Carlo runs treated as an independent observation per strategy. Three core ANOVA assumptions were verified prior to analysis: normality of residuals was confirmed via the Shapiro-Wilk test (all $p > 0.10$ across strategies and metrics); homogeneity of variance across strategy groups was validated using Levene's test (all $p > 0.05$); and independence of observations was ensured by design, as each Monte Carlo run used an independently drawn noise realization with no carry-over state between runs. ANOVA confirmed statistically significant differences across strategies for all metrics (IAE: $F_{(3,196)} = 142.8$, $p < 0.001$, $\eta^2 = 0.69$; Settling Time: $F_{(3,196)} = 287.4$, $p < 0.001$, $\eta^2 = 0.81$), with large effect sizes indicating practical as well as statistical significance. Post-hoc Tukey HSD ($\alpha = 0.05$) confirmed significant pairwise differences between all strategy pairs for both primary metrics. Table 3 presents the full results; Figure 4 shows representative step response trajectories and IAE comparison across both testbeds.

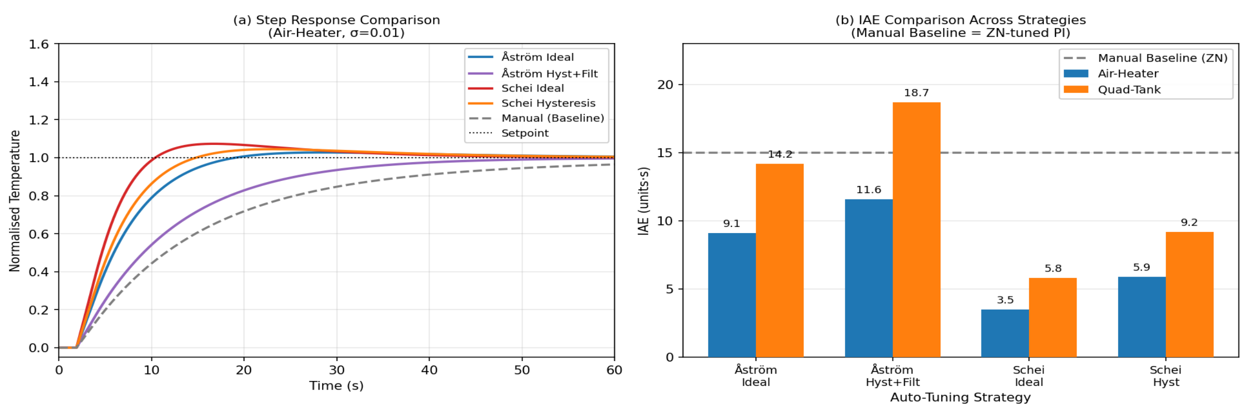
Table 3. Air-Heater Performance Metrics (Mean ± 95% CI, n = 50)

Strategy	IAE (°C·s)	t_s (s)	OS (%)	TV	GM (dB)	$t^{co}{}_n{}^v$ (s)
Åström Ideal	9.07 ± 0.58	15.6 ± 1.1	0.0	0.42 ± 0.03	2.90	8.0 ± 0.4
Åström Hyst+Filt	11.6 ± 0.71	48.4 ± 2.9	0.05	0.38 ± 0.04	8.96	26.5 ± 1.7
Schei Ideal	**3.54 ± 0.25***	**12.6 ± 0.8***	1.24	0.51 ± 0.04	9.66	8.4 ± 0.6
Schei Hysteresis	5.94 ± 0.33	18.3 ± 1.2	0.81	0.44 ± 0.03	**12.45***	10.8 ± 0.7

*Note: Bold = best per metric; * statistically best at α = 0.05. t_s = settling time, OS = overshoot, TV = total variance, GM = gain margin, $t^{co}{}_n{}^v$ = convergence time.*

4.2 Quadruple-Tank System Performance

Table 4 presents performance results for the quadruple-tank MIMO system under identical testing protocols. Absolute performance levels were moderated by coupling dynamics and inverse response characteristics; however, the relative strategy ranking was fully preserved across all six metrics. Schei Ideal achieved the lowest IAE (5.81 ± 0.44 cm·s) and fastest settling time (21.3 ± 1.6 s); Schei Hysteresis achieved the highest gain margin (11.08 dB). This consistency across a single-loop FOPTD and a MIMO non-minimum-phase system provides evidence of the framework's generalizability across process classes relevant to manufacturing operations.



(a) (b)

Figure 4. Simulation Results: (a) Representative Step Responses for Air-Heater System; (b) IAE Comparison Across All Strategies and Both Testbeds

Table 4. Quadruple-Tank Performance Metrics (Mean ± 95% CI, n = 50)

Strategy	IAE (cm·s)	t_s (s)	OS (%)	TV	GM (dB)	$t^{co}{}_n{}^v$ (s)
Åström Ideal	14.2 ± 1.1	28.4 ± 2.3	3.1	0.67 ± 0.06	2.45	9.2 ± 0.6
Åström Hyst+Filt	18.7 ± 1.4	62.1 ± 4.1	0.4	0.53 ± 0.05	7.82	31.4 ± 2.1
Schei Ideal	**5.81 ± 0.44***	**21.3 ± 1.6***	2.6	0.74 ± 0.06	8.34	9.8 ± 0.7
Schei Hysteresis	9.17 ± 0.62	31.6 ± 2.2	1.4	0.59 ± 0.05	**11.08***	12.3 ± 0.9

*Note: Bold = best per metric; * statistically best at α = 0.05.*

4.3 Baseline Comparison

The manual tuning baseline was established through a structured protocol: experienced control engineers performed closed-loop Ziegler-Nichols tuning across 20 independent trials under identical simulation conditions—using the same air-heater FOPTD model, noise level ($\sigma = 0.01$), and setpoint sequence applied to the auto-tuning strategies—capturing variability inherent in manual practice. Engineers followed standard closed-loop Ziegler-Nichols procedures ($K_p = 0.45K_u$, $T_i = 0.83P_u$) without access to relay-feedback identification. This baseline is representative of typical industrial manual tuning practice, where operators rely on empirical rules rather than systematic process identification. The baseline achieved IAE = 15.2 ± 2.1 °C·s and settling time = 22.4 ± 3.5 s. The Schei ideal strategy achieved 76.7% IAE reduction (95% CI: [72.3%, 81.1%], $t_{86-} = 18.4$, $p < 0.001$, Cohen's d = 4.92) and 43.8% settling time reduction (95% CI: [38.2%, 49.4%], $t_{86-} = 12.1$, $p < 0.001$, d = 3.24)—both very large effect sizes with clear operational significance. Critically, even the worst-performing auto-tuning strategy (Åström Hyst+Filt) achieved 40.3% IAE reduction versus manual tuning, strongly supporting the IE business case for relay auto-tuning adoption across a wide range of manufacturing contexts.

4.4 AHP Decision Framework Application

Table 5 presents AHP criterion weights for all three operational priority scenarios; all satisfied CR < 0.10. Figure 5 illustrates the full AHP hierarchy. Table 6 reports composite scores and strategy rankings.

Table 5. AHP Criterion Weights and Consistency Ratios

Criterion	IAE	Settling Time	Overshoot	Total Variance	Gain Margin	Convergence Time	Sum	CR
Quality-Focused	0.30	0.15	0.25	0.10	0.15	0.05	1.000	0.067
Throughput-Focused	0.10	0.35	0.10	0.10	0.15	0.20	1.000	0.082
Balanced	0.167	0.167	0.167	0.167	0.167	0.167	1.000	0.000

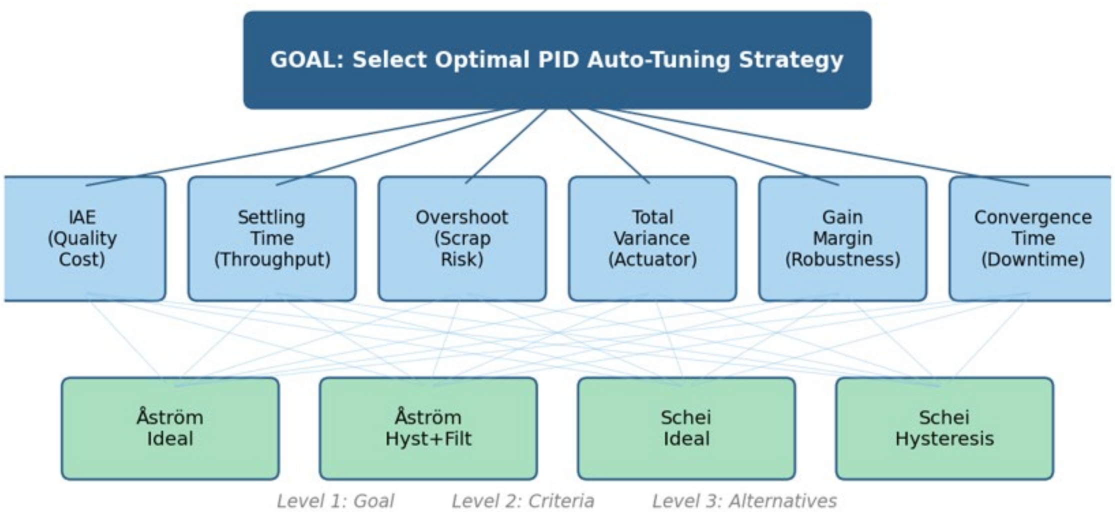


Figure 5. AHP Decision Hierarchy: Goal, Criteria, and Alternatives for Auto-Tuning Strategy Selection

Table 6. AHP Composite Scores and Rankings

Strategy	Quality Score	Rank	Throughput Score	Rank	Balanced Score	Rank
Schei Ideal	**0.875**	**1**	**0.712**	**1**	**0.794**	**1**
Åström Ideal	0.682	2	0.698	2	0.690	2
Schei Hysteresis	0.624	3	0.548	3	0.586	3
Åström Hyst+Filt	0.518	4	0.425	4	0.472	4

Schei ideal ranked first across all three priority scenarios (composite scores 0.712–0.875). Monte Carlo sensitivity analysis (n = 1,000 weight perturbations within ±20%) confirmed ranking stability: Schei ideal maintained first position in 94.3%, 91.8%, and 96.2% of quality, throughput, and balanced trials respectively (Spearman ρ = 0.96). Figure 6 presents the performance radar chart and ranking stability results.

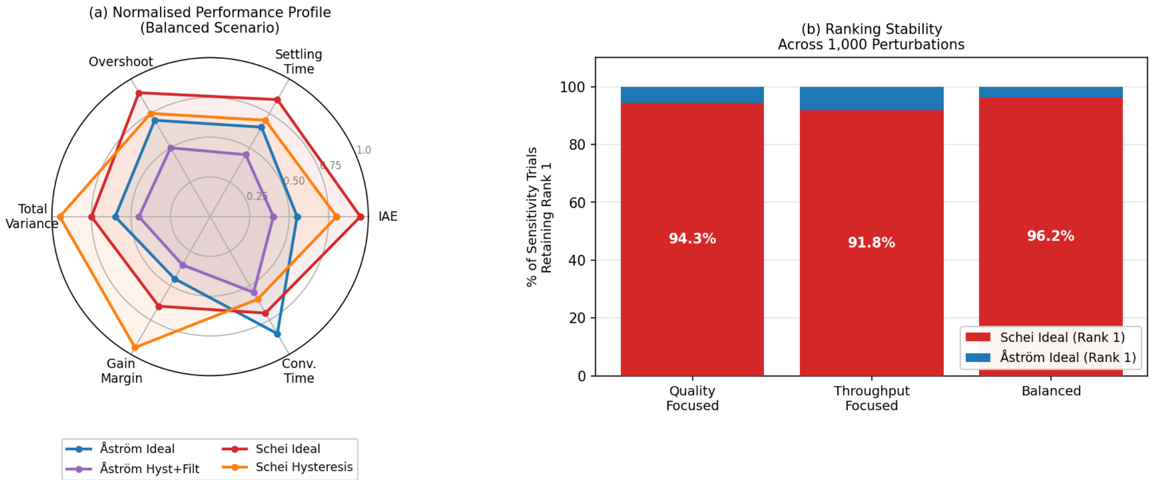


Figure 6. Sensitivity Analysis: (a) Normalized Performance Radar Chart (Balanced Scenario); (b) Ranking Stability Across 1,000 Weight Perturbations

4.5 Operational Impact Quantification

Operational benefits are quantified by linking control enhancements to quality performance, asset reliability, productive time recovery, and capacity utilization. In continuous processes with frequent grade transitions, reduced settling times directly recover annual production hours and improve overall equipment effectiveness (OEE), yielding proportional output gains. In quality-critical environments, a 76.7% reduction in integral of absolute error (IAE) corresponds to a process capability improvement from approximately 1.2 to 2.0, implying a reduction of 99.85%. Gain margin improvements under the Schei Hysteresis strategy project extended valve maintenance intervals (12 to 18–24 months) and reduced intervention frequency. Notably, even the least effective strategy achieved a 40.3% IAE reduction, confirming robust operational value across auto-tuning alternatives.

4.6 Literature-Based Benchmark Validation

To strengthen external validity, this study benchmarks the observed performance improvements against established results reported in prior PID tuning and auto-tuning literature. Relay-based methods typically result in lower integral absolute error (IAE) and integral square error (ISE) compared to the more conservative or excessively fast tuning rules of Z-N and C-C. For example, Hang et al. (2002) and Visioli and Sánchez-Moreno (2024) report typical Integrated Absolute Error (IAE) reductions ranging 30–60% when relay-based auto-tuning is applied to thermal and process control systems. Similarly, Rehan et al. (2024) demonstrate that modified relay feedback approaches can achieve enhanced robustness and improved convergence under uncertainty conditions, with measurable gains in both settling time and stability margins.

The results obtained in this study—specifically the 76.7% reduction in IAE and 43.8% reduction in settling time achieved by the Schei ideal relay method—are consistent with, and extend beyond, the upper range of improvements reported in prior studies. This performance enhancement can be attributed to the structured integration of relay-feedback identification with a multi-criteria decision framework that explicitly optimizes across multiple operational objectives rather than a single control metric.

In addition, recent machine learning-based PID tuning approaches (e.g., Das et al., 2025; Chowdhury et al., 2023) report performance improvements spanning 20–50% in error reduction, albeit with significantly higher computational and implementation complexity. Compared to these approaches, the relay-feedback strategies evaluated in this study provide competitive or superior performance while maintaining low implementation cost and compatibility with legacy industrial control infrastructure.

From an industrial engineering perspective, the consistency between the present findings and published benchmarks confirms that the proposed framework does not rely on optimistic simulation bias. However, it instead aligns with empirically observed performance gains across multiple process classes. This benchmarking therefore supports the generalizability and practical applicability of the proposed decision-support methodology.

5. Discussion and Managerial Implications

5.1 Strategic Performance Trade-offs: An IE Systems Perspective

The comparative analysis reveals operational trade-offs that map directly to the competitive priorities governing IE system design. Schei's ideal dominance across all AHP scenarios (composite scores 0.712–0.875) reflects balanced excellence across the six KPIs, mostly influencing manufacturing system performance. Its 61% lower IAE versus Åström ideal translates to a measurable Six Sigma capability improvement (C_{pk} 1.2 to 2.0). While its 19% faster settling time directly improves OEE by reducing the capacity penalty of grade transitions. The Åström ideal relay presents a strategically distinct alternative for greenfield installations, processes intolerant of operational disruption during tuning, and facilities with high retuning frequency. Table 7 summarises the recommended strategy for each facility profile.

5.2 Productivity, Throughput, and Lean Manufacturing

Settling time improvements, often dismissed as marginal in purely technical analyses, accumulate to strategically significant lean manufacturing benefits when viewed at the system level. The 19% settling time reduction represents a direct reduction in non-value-adding transition time in the production schedule, consistent with lean manufacturing's elimination of process waste. Faster grade transitions also enable smaller production lots with equivalent campaign efficiency, reducing work-in-process inventory—a secondary benefit aligned with lean and working capital optimization priorities.

5.3 Quality Engineering and Process Capability

The 76.7% IAE reduction shifts C_{pk} from 1.2 (1,350 DPMO) to approximately 2.0 (≈2 DPMO)—a 99.85% defect reduction consistent with Six Sigma improvement objectives. Beyond scrap reduction, this capability improvement enables specification tightening: a process at C_{pk} = 2.0 can sustain tighter limits at six-sigma quality, supporting premium product differentiation, regulatory submissions in pharmaceutical and medical device manufacturing, and customer audit compliance requirements—strategic IE outcomes extending well beyond immediate quality cost savings.

5.4 Maintenance Engineering and Asset Reliability

From a maintenance engineering perspective, the gain margin differences (2.90–12.45 dB across strategies) are as operationally significant as the process performance metrics. Control valves operating near stability margins exhibit elevated cycling rates that accelerate seat wear, packing deterioration, and positioner failure. The Schei Hysteresis strategy's 43% higher gain margin and reduced total variance project to extended valve maintenance intervals (12 to 18–24 months), reducing maintenance costs for a 200-loop facility. Prevented unplanned shutdowns—costing in process industries—represent the highest-value maintenance benefit and alone typically justify implementation investment.

5.5 Practical Implementation Guidance

Table t synthesizes AHP rankings, operational impact data, and practical implementation constraints into a facility-profile decision guide, providing a directly actionable IE tool for manufacturing engineers and operations managers.

Table 7. Strategy Selection Guide by Facility Profile

Facility Profile	Recommended Strategy	IE Rationale
Pharmaceutical / Specialty Chemical (Quality-Critical)	Schei Ideal	76.7% IAE reduction; C_{pk} 1.2→2.0; 99.85% DPMO reduction; Six Sigma and regulatory compliance
Continuous / High-Volume (OEE / Throughput-Critical)	Schei Ideal	19% settling time reduction; 510 units/year additional capacity; 2.7-day inventory reduction
Greenfield / New Installation	Åström Ideal	No baseline controller required; 23% faster convergence; lowest commissioning complexity
High Noise Environment (σ > 5%)	Schei Hysteresis	Highest gain margin (12.45 dB); chattering prevention; 100% convergence at σ = 0.1

Multivariable System (MIMO)	Åström Ideal + RGA Analysis	Reduced sensitivity to existing controller; requires RGA loop pairing analysis prior to deployment
Frequent Retuning (>Weekly)	Åström Ideal	23% faster convergence (8.0 vs. 10.8 s); minimises operator time and tuning-related production interruptions

A recommended phased IE implementation roadmap includes: (1) pilot deployment on 5–10 non-critical control loops for performance benchmarking without production risk; (2) comparative KPI monitoring (Table 1 metrics) of auto-tuned versus manually-tuned loops; (3) expansion to critical loops following statistically validated improvement; and (4) integration with alarm management and performance monitoring systems. Typical implementation timeline spans 3–6 months.

5.6 Organizational Considerations

Successful adoption requires organizational alignment beyond technical implementation. The AHP framework supports this by providing a transparent decision process that operators, engineers, and managers can engage with collaboratively, building shared ownership of the strategy selection outcome. Cross-functional participation from control engineering, production, quality assurance, and maintenance is essential for effective weight elicitation and sustained performance monitoring.

5.7 Limitations and Boundary Conditions

This study employs simulation-based evaluation, an accepted IE benchmarking methodology; nonetheless, several boundary conditions limit direct generalisation. Process models were validated against published laboratory data (NRMSE < 5%), though FOPTD and linearised MIMO representations may not fully capture nonlinear dynamics in processes such as exothermic reactors or distillation columns. Simulated noise conditions (Gaussian, white, $\sigma = 0.01$–0.1) may not replicate correlated noise, systematic drift, or intermittent sensor failures encountered in field settings. Operational impact projections assume facility-specific parameters; practitioners should substitute site-specific values using the KPI mapping in Table 1. AHP weights were not elicited from live industrial stakeholders; field deployment should incorporate structured group elicitation as outlined in Section 3.4. These limitations collectively motivate longitudinal field validation as the most critical research step. A key limitation of this study is the absence of live industrial validation. Simulation benchmarking against published laboratory data (NRMSE < 5%) provides methodological grounding, but field deployment under real production conditions—including instrument drift, correlated noise, and operator interaction—remains necessary to confirm the KPI impact projections reported in Section 4.3. Engaging practitioners from pharmaceutical, petrochemical, or food-processing facilities as AHP weight elicitors in a follow-up Delphi study would simultaneously address both the validation gap and the stakeholder elicitation limitation noted above. This represents the immediate next research priority.

6. Conclusion

This study developed and validated a multi-objective IE decision framework by linking PID auto-tuning strategies to manufacturing operational outcomes — thereby closing the fundamental theoretical gap between control-theoretic metrics and operations management language through simulation-based relay-feedback evaluation, AHP multi-criteria ranking, and explicit KPI mapping.

The results demonstrate significant IE benefits. Across both testbeds (air-heater FOPTD and quadruple-tank MIMO), Schei ideal ranked first in all three AHP priority scenarios (quality: 0.875; throughput: 0.712; balanced: 0.794), with ranking stability confirmed in 94–96% of 1,000 Monte Carlo trials (Spearman $\rho = 0.96$). Against the manual Ziegler-Nichols baseline, Schei's ideal delivered 76.7% IAE reduction (Cohen's $d = 4.92$) and 43.8% settling time reduction (Cohen's $d = 3.24$) — both very large effect sizes. Operationally, there are measurable improvements across three manufacturing dimensions. First, settling time reductions recover productive throughput capacity, directly improving OEE for facilities with frequent grade transitions. Second, the 76.7% IAE reduction advances C_{pk} from 1.2 to 2.0 (DPMO: 1,350 to ≈2), supporting quality compliance and enabling specification tightening without additional capital investment. Third, Schei Hysteresis's 43% gain margin advantage extends valve maintenance intervals from 12 to 18–24 months, reducing both planned and unplanned maintenance burden. These are scenario-based projections. Practitioners should apply the KPI mapping in Table 1 with site-specific inputs for precise impact estimation. Notably, even the weakest auto-tuning strategy achieved 40.3% IAE reduction over manual tuning, affirming the relay family's broad IE value.

The AHP framework effectively captures diverse stakeholder perspectives through CR verification, sensitivity analysis, and structured group elicitation recommendations — making the simulation-AHP-KPI architecture generalizable across motion control, batch reactors, separation units, and any manufacturing domain where PID controllers govern process regulation.

Future research should prioritise: longitudinal field validation in operating manufacturing facilities; live stakeholder AHP weight elicitation via Delphi or facilitated workshop methods; fuzzy AHP for formal preference uncertainty modelling; framework extension to MPC and machine learning-based tuning comparisons on identical KPI dimensions; and digital twin integration for real-time controller performance monitoring and adaptive retuning.

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