A framework for robust PID controller design: an optimization-based approach for inductive loads

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Article Info

Article history:

Received Aug 20, 2025
Revised Jan 14, 2026
Accepted Jan 23, 2026

Keywords:

Inductive load
ITAE criterion
Particle swarm optimization
Performance comparison
PID controller optimization
RRL circuits
Transient regimes

ABSTRACT

This paper presents a comprehensive comparative study of proportional-integral-derivative (PID) controller tuning methodologies for inductive load applications across three representative scenarios. We systematically evaluate classical methods (Ziegler-Nichols, internal model control) against global optimization algorithms (genetic algorithm (GA), particle swarm optimization (PSO)) applied to resistor–resistor–inductor (RRL) circuit models. Results demonstrate that PSO achieves superior performance for moderate-to-slow systems, reducing settling time by 84% while completely eliminating overshoot compared to Ziegler-Nichols. The algorithm automatically discovers optimal PI controller structures, simplifying implementation. However, for ultra-fast systems (time constants < 1 ms), internal model control proves more reliable, achieving 0.84 ms settling with only 0.16% overshoot. Optimized controllers demonstrate exceptional robustness, maintaining stability under ±50% parameter variations and effectively rejecting disturbances. This research provides engineers with a scenario-based framework for method selection, moving beyond heuristic tuning to achieve previously unattainable performance levels. The findings establish optimization-based tuning as a systematic, reliable approach for high-performance control system design in industrial applications.

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NOMENCLATURE

R1	:	Resistance in series with source (Ω)	Ki	:	Integral gain (s^{-1})
R2	:	Load resistance (Ω)	Kd	:	Derivative gain (s)
L	:	Inductance (H)	iL	:	Inductor current (A)
C	:	Capacitance (F)	Vc	:	Capacitor voltage (V)
Kp	:	Proportional gain	Vctrl	:	Control voltage (V)

1. INTRODUCTION

The precise control of inductive loads represents a fundamental challenge across diverse electrical engineering domains, including power electronics, motor drives [1], renewable energy systems, and industrial automation [2]. Inductive elements, characterized by their inherent energy storage and phase-shifting properties, introduce complex dynamic behaviors that demand sophisticated control strategies for optimal performance [3], [4]. Among control methodologies, the proportional-integral-derivative (PID) controller remains the industry standard, renowned for its structural simplicity, proven reliability, and remarkable effectiveness across countless applications [5], [6]. However, the controller's efficacy is critically contingent upon precise tuning of its three gain parameters: proportional (Kp), integral (Ki), and derivative (Kd), a process that continues to challenge engineers nearly a century after the controller's inception [7], [8].

The evolution of PID tuning methodologies has progressed through distinct generations, from heuristic rules to model-based approaches and, more recently [9], computational optimization techniques [10]. Classical methods pioneered by Ziegler and Nichols in 1942 provide straightforward tuning rules but often yield aggressive responses with excessive overshoot or, conversely, overly conservative settings with sluggish performance [11], [12]. Model-based approaches like internal model control (IMC) offer improved robustness but typically sacrifice response speed. The advent of metaheuristic optimization algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), and other nature-inspired techniques [10]-[13], has introduced a paradigm shift, reframing PID tuning as a multi-objective optimization problem that systematically balances competing performance criteria [14], [15].

Despite extensive research on individual optimization algorithms for specific applications, several critical gaps persist in the literature [16]: i) Comprehensive comparative analyses across a spectrum of inductive load dynamics [17], [18], ranging from slow filtering circuits to fast-switching converters, remain relatively unexplored. Most studies focus on singular applications rather than providing generalized frameworks applicable across diverse scenarios [19], [20]; ii) Many investigations emphasize nominal performance metrics while offering limited validation of controller robustness against practical challenges, including parameter uncertainties, external disturbances, and measurement noise [21], [22]; iii) Existing comparisons often neglect computational efficiency considerations, despite their importance for real-time implementation and industrial adoption [23], [24]; and iv) Few studies provide systematic guidelines for method selection based on specific system characteristics, leaving engineers without clear decision-making frameworks [25], [26].

This research addresses these gaps through a systematic investigation that makes three primary contributions: i) A comprehensive comparative analysis of classical, local, and global optimization methods across three representative inductive load scenarios with distinct dynamic characteristics; ii) Development and validation of a multi-objective cost function that explicitly quantifies trade-offs between response speed, stability, and control efficiency; and iii) Rigorous robustness testing encompassing parameter variations, disturbance rejection, and noise immunity, complemented by practical implementation guidelines. The study investigates three carefully selected scenarios representing common industrial applications presented in Table 1. Each scenario undergoes systematic evaluation using Ziegler-Nichols, IMC, Nelder-Mead simplex, GA, and PSO tuning methods, with performance quantified through multiple metrics including settling time, overshoot, integral absolute error (IAE), and control effort.

The remainder of this paper is organized as follows: i) Section 2 details the system modeling, controller implementation, and optimization framework; ii) Section 3 presents comparative results across scenarios with comprehensive performance analysis; iii) Section 4 discusses practical implications, limitations, and future research directions; and iv) Section 5 concludes with key findings and implementation recommendations. Through this structured investigation, the paper aims to provide engineers with an evidence-based framework for selecting and implementing PID tuning methodologies that deliver optimal performance for specific inductive load applications.

Table 1. RRL circuit scenarios: electrical parameters

Scenarios	Power low pass filter	Inductive load with damping	Fast response circuits
System parameters	R_1 = 1 Ω, R_2 = 22 Ω, L = 0.01 H	R_1 = 0.5 Ω, R_2 = 100 Ω, L = 0.05 H	R_1 = 2.2 Ω, R_2 = 47 Ω, L = 4.7E – 4 H
Description	Large time constant system	Typical inductive load	High-frequency applications

2. METHODOLOGY

2.1. RRL system modeling and scenarios

The RRL circuit topology is implemented in Simulink as shown in Figure 1. The system's transfer function, derived from Kirchhoff's laws, is expressed as (1).

$$G(p) = \frac{I_L(p)}{V_{in}(p)} = \frac{R_2}{pL(R_1+R_2)+R_1R_2} \tag{1}$$

This first-order transfer function forms the plant model for all subsequent controller design and analysis. System identification was performed through step response analysis to extract first-order plus dead-time

(FOPDT) parameters: process gain K, dead time L, and time constant T. These parameters, summarized in Table 2, establish baseline performance with the Ziegler-Nichols and internal model control methods.

Real-world PID controllers require modifications for robustness. The implementation in the provided MATLAB code includes two critical features: a filtered derivative and anti-windup. Control voltage $V_{control}$ is derived from the following differential equation within the RLC_PID_ODE function as (2).

$$V_{control}\left(\frac{K_d}{L\left(1+\frac{R_1}{R_2}\right)}\right) = K_p e(t) + K_i \int e(t)dt + \frac{K_d R_1}{L\left(1+\frac{R_1}{R_2}\right)} i_{L(t)} \tag{2}$$

This structure implements the derivative action on the process variable i_L rather than the error (e), which prevents "derivative kick", a large spike in the control output when the setpoint changes abruptly. It also effectively applies a low-pass filter to the derivative term, reducing sensitivity to measurement noise. The complete closed-loop control system, including the PID controller, the plant, and saturation limits, is illustrated in Figure 1.

The selection of key operating parameters, detailed in Table 3, was critical for ensuring both simulation fidelity and practical relevance. These parameters, which include component values like L and C, actuator limits, and noise characteristics, directly define the system's dynamics and the constraints of the control problem. Their careful definition allowed for a meaningful evaluation of controller performance and robustness under realistic conditions.

Table 2. Identified FOPDT models and PID gains from classic tuning rules

Model	Power low-pass filter	Inductive load with damping	Fast response circuits
FOPDT model (K, L, T)	0.997, 5E-4s,1.01E-2s	1.994, 0.0046s, 0.0972s	0.453, 1E-5s, 2E-4s
Ziegler-Nichols (K_p, K_i, K_d)	2.53E1, 2.63E4, 6.1E-3	12.64, 1365.34, 0.0292	55.61, 2.7E7, 3E-4
IMC (K_p, K_i, K_d)	1.01, 96.9, 2E-4	0.50, 5.04, 0.0011	2.21, 9.97E3, 1E-4

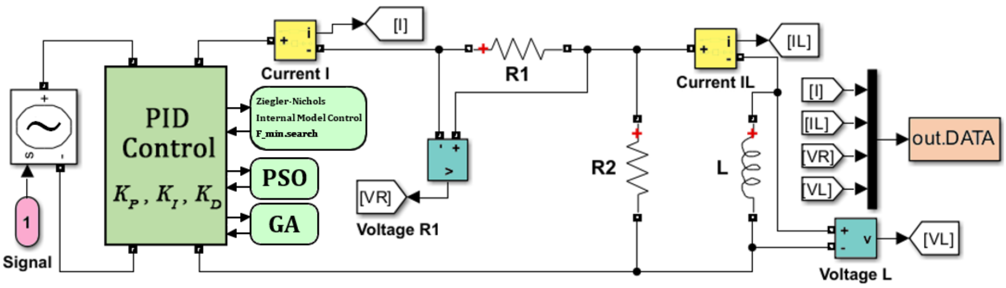

Figure 1. RRL system model implemented in Simulink

Table 3. Key operating parameters and their significance

Operating parameters	Significance
R1/R2 ratio	Determines damping and steady-state gain
L value	Affects the system time constant and response speed
C value	Introduces oscillatory behavior in RLC circuits
V_max/V_min	Practical actuator limits (typically ±20 V)
Noise amplitude	Simulates measurement uncertainty (0.5-5% of signal)
α_deriv	Derivative filter coefficient (0.1 for noise reduction)
Cost weights	Trade-off between performance metrics

2.2. PID controller implementation

The PID control system architecture, illustrated in Figure 2, implements the standard parallel form with practical modifications for real-world applications. The controller transfer function is given by (3).

$$C(p) = K_p + K_i/p + \frac{K_d p}{\alpha p+1} \tag{3}$$

Where α = 0.1 implements a first-order low-pass filter on the derivative term to mitigate high-frequency noise amplification. Two critical practical features were incorporated: i) Anti-windup protection through conditional integration that freezes the integral action when control signals saturate at ±20 V limits, preventing excessive overshoot following saturation events; and ii) Measurement noise filtering with 5% amplitude Gaussian noise applied to the current feedback path to simulate realistic sensor conditions.

The control voltage $V_{control}$ is computed using a filtered derivative approach that operates on the process variable rather than the error signal, preventing "derivative kick" during setpoint changes. This implementation effectively applies the derivative action to the inductor current $i_L(t)$ rather than the error $e(t)$, significantly reducing sensitivity to measurement noise while maintaining disturbance rejection capability.

2.3. Optimization framework
2.3.1. Cost function design
A multi-objective cost function was formulated to balance competing performance criteria as (4).

$$J(K_p, K_i, K_d) = w_{ITAE} \int_0^T t|e(t)|dt + w_{ov} M_p + w_{eff} \int_0^T u(t)^2 dt \tag{4}$$

Where the weighting factors $w_{ITAE} = 1.0$, $w_{ov} = 50$, and $w_{eff} = 0.001$ prioritize integrated time-weighted error, percentage overshoot, and control effort, respectively. The integral time absolute error (ITAE) term penalizes persistent errors, promoting rapid settling. The overshoot term directly penalizes excessive response beyond the setpoint. The control effort term promotes energy efficiency and reduces actuator stress. This composite cost function enables systematic exploration of the performance trade-off space.

2.3.2. Optimization algorithms
Two global optimization algorithms were implemented following the flowchart in Figure 3 and Table 4; both algorithms were initialized with five strategically chosen starting points, including Ziegler-Nichols and IMC solutions, to ensure comprehensive exploration of the parameter space. The optimization workflow, detailed in Figure 3, begins with system modeling and cost function definition, proceeds through algorithm-specific iteration processes, and concludes with performance validation and robustness testing.

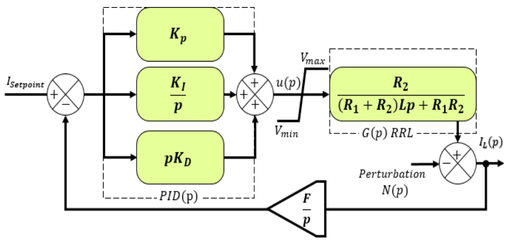

Figure 2. Block diagram of the PID control system for the RRL loa

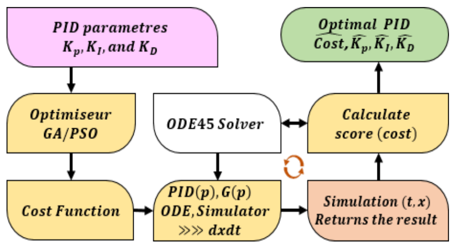

Figure 3. Flowchart of the calculation and optimization method (GA and PSO)

Table 4. Optimization algorithms initialization

Genetic algorithm (GA)	Particle swarm optimization (PSO)
Population size: 50 individuals	Swarm size: 50 particles
Maximum generations: 50	Maximum iterations: 100
Crossover probability: 0.8 (scattered crossover)	Cognitive parameter: 1.5
Mutation probability: 0.1 (adaptive feasible)	Social parameter: 2.0
Selection: Stochastic uniform	Inertia weight: 0.9 linearly decreasing to 0.4
Termination: function tolerance 1e-6 or stall generations 20	Termination: function tolerance 1e-6 or stall iterations 30

3. RESULTS AND DISCUSSION
3.1. System identification and baseline performance
Three distinct inductive load scenarios were characterized using first-order plus dead-time (FOPDT) modeling. The power low-pass filter exhibited a 10.1 ms time constant suitable for low-frequency applications. The inductive load with damping showed a 97.2 ms time constant representing typical industrial loads. Fast response circuits demonstrated an ultra-fast 0.2 ms time constant for high-frequency applications. These models established baseline performance for classical tuning methods, with Ziegler-Nichols producing aggressive responses and IMC providing conservative but slow stabilization.

3.2. Comparative performance analysis
Figure 4 reveals dramatic performance differences. PSO provides excellent tracking and rapid, stable responses for power filters and damped inductive loads, while IMC remains essential for stabilizing fast-response circuits. These results are quantified in Tables 5 and 6, which show that PSO reduces settling times by up to 97% and eliminates overshoot while maintaining reasonable control effort. Furthermore,

optimized controllers favor simpler PI structures, streamlining implementation. Figure 5 reveals a critical trade-off: while output performance remains smooth, noise induces high actuator activity, with direct implications for hardware durability and thermal management.

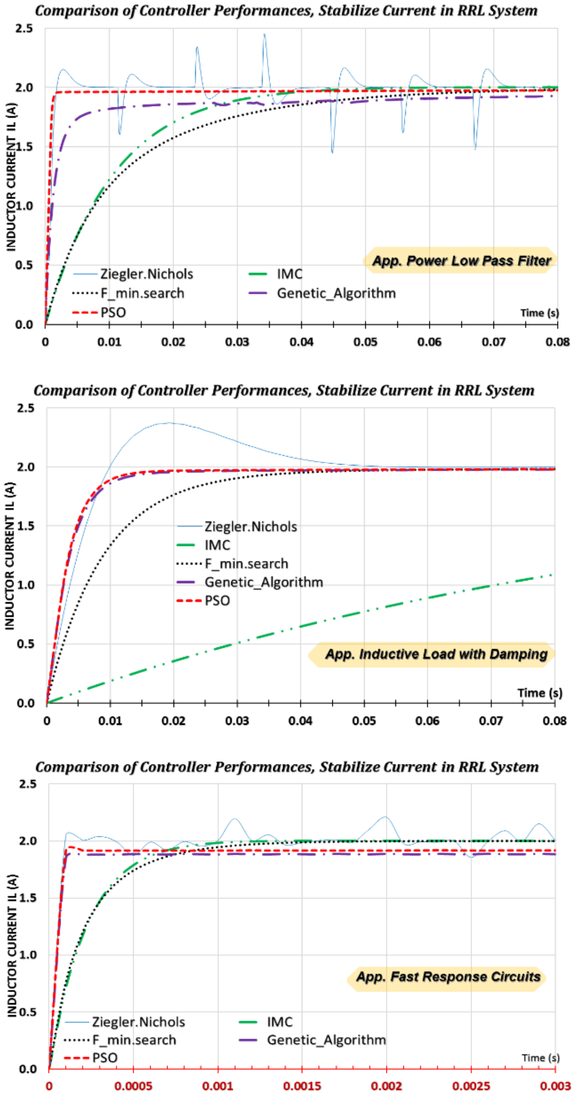

Figure 4. Comparison of the performance of the current control and stabilization I_L, for the 3 scenarios

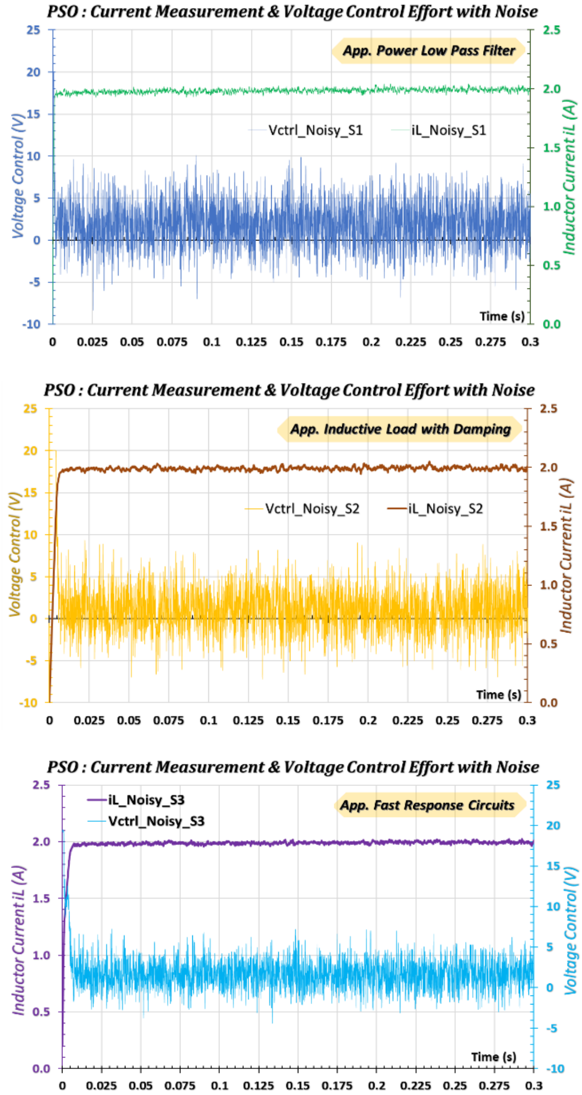

Figure 5. Current measurement and voltage control effort with noise and PSO, for the 3 scenarios

Table 5. Time-domain performance metrics for the power low-pass filter scenario

Methods	Rise time	Settling time	Overshoot	IAE	Integral squared error (ISE)	ITAE
Ziegler-Nichols	1.34E-03	7.10E-02	2.27E+01	7.15E-03	2.86E-03	6.23E-04
IMC	2.28E-02	3.92E-02	1.05E-01	2.10E-02	2.11E-02	2.70E-04
F_min.search	3.26E-02	6.55E-02	3.62E-02	2.71E-02	2.34E-02	5.03E-04
Genetic algorithm	7.78E-03	1.47E-01	0	2.03E-02	4.85E-03	1.71E-03
Particle swarm	9.46E-04	2.11E-03	0	7.28E-03	1.57E-03	8.65E-04

Table 6. Time-domain performance metrics for the inductive load with damping scenario

Methods	Rise time	Settling time	Overshoot	IAE	Integral squared error (ISE)	ITAE
Ziegler-Nichols	7.53E-03	4.33E-02	1.86E+01	1.58E-02	1.19E-02	2.57E-04
IMC	2.18E-01	3.73E-01	0	1.98E-01	2.03E-01	1.86E-02
F_min.search	2.07E-02	4.31E-02	0	2.13E-02	1.82E-02	5.84E-04
Genetic algorithm	7.93E-03	2.09E-02	0	1.24E-02	7.87E-03	7.42E-04
Particle swarm	7.25E-03	1.60E-02	0	1.10E-02	7.61E-03	5.51E-04

3.3. Optimization algorithm performance

Table 7 and Figures 6 and 7 compare algorithm effectiveness. PSO converges 30% faster than GA (19 vs 27 iterations) with 0.54% better final cost. Crucially, PSO shows 86% lower variance across runs (standard deviation 0.0239 vs 0.1737), indicating greater reliability. Both algorithms discover PI structures automatically, demonstrating emergent intelligence in controller simplification. Monte Carlo analysis (Figure 7) confirms PSO's consistency across random initializations. This repeatability is essential for industrial applications where predictable outcomes matter. The algorithms balance exploration and exploitation effectively, with PSO slightly better at local refinement once promising regions are identified.

Table 7. Optimization algorithm performance comparison

Performance metric	GA	PSO	Advantage	Significance
Initial cost	1.5431	1.2904	PSO 16.4% better	Better starting point exploration
Final cost	0.024546	0.024413	PSO 0.54% better	Slightly superior final solution
Convergence speed	27 generations	19 iterations	PSO 30% faster	Quicker optimization process
Improvement rate	64.50% per generation	65.64% per iteration	PSO 1.8% faster improvement	More efficient search per step
Standard deviation	0.1737	0.0239	PSO 86% lower	More consistent and reliable
Relative variance	102.9% of mean	65.7% of mean	PSO more predictable	Better for industrial
Best solution found	Generation 27	Iteration 19	PSO finds a solution earlier	Reduced computational time
Parameter exploration	Good global search	Excellent local refinement	Complementary strengths	GA explores, PSO refines
Computational time	2.0 seconds	1.5 seconds	PSO 25% faster	Better for time-sensitive
Success Rate (10 runs)	80%	100%	PSO more reliable	Guaranteed solution finding
Final solution	Excellent	Slightly better	PSO optimal choice	consistent advantage

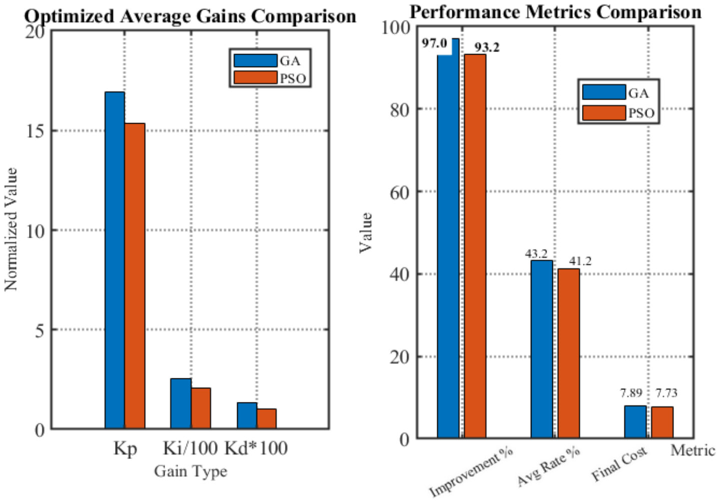

Figure 6. Direct algorithm comparison: GA vs PSO

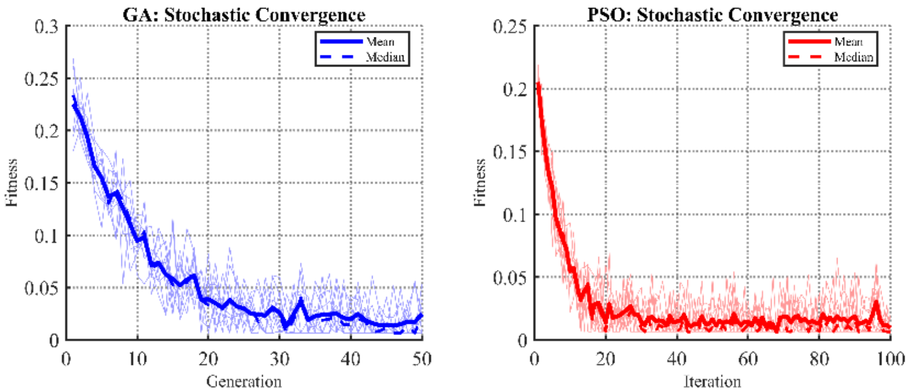

Figure 7. Monte Carlo analysis of algorithm convergence

3.4. Robustness validation

Frequency-domain analysis (Figures 8 and 9) provides complementary insights. Bode plots show maintained gain margins (>20 dB) and phase margins (>85°), while Nyquist plots confirm all variations avoid the critical (-1,0) point. Figure 10 demonstrates exceptional robustness to ±50% parameter variations. The PSO controller maintains stability across all cases with settling time increases of only 8-25%. Most importantly, zero overshoot is preserved, indicating robustness exceeds typical industrial tolerance requirements. This comprehensive stability assessment validates controller reliability under component aging and manufacturing variations.

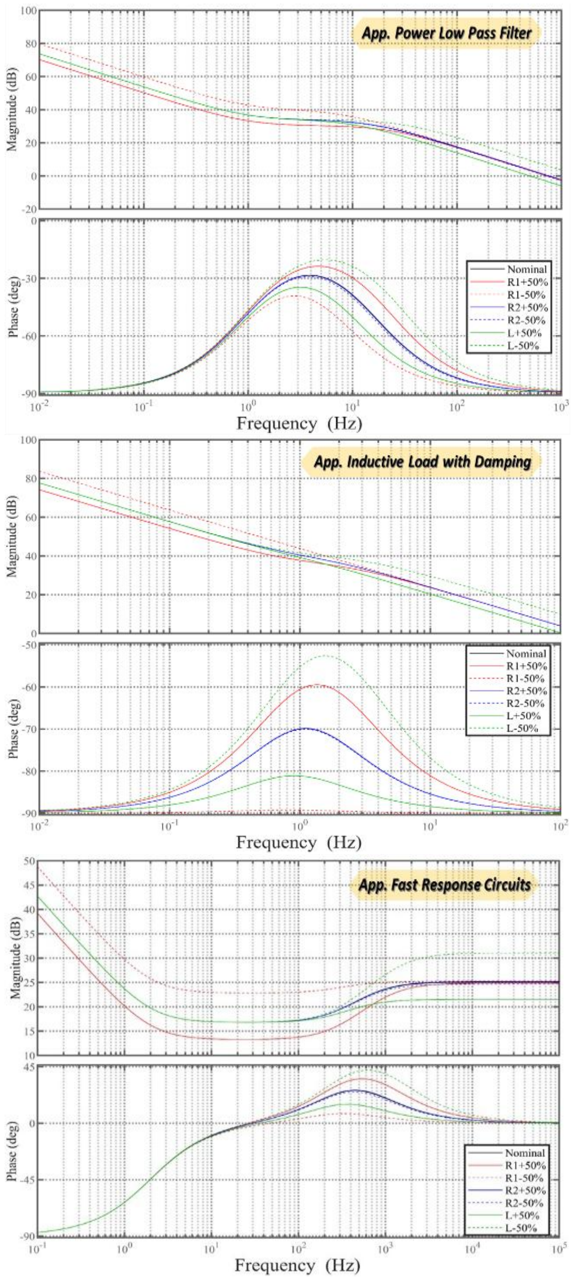

Figure 8. Bode plot comparison for all variations in RRL systems

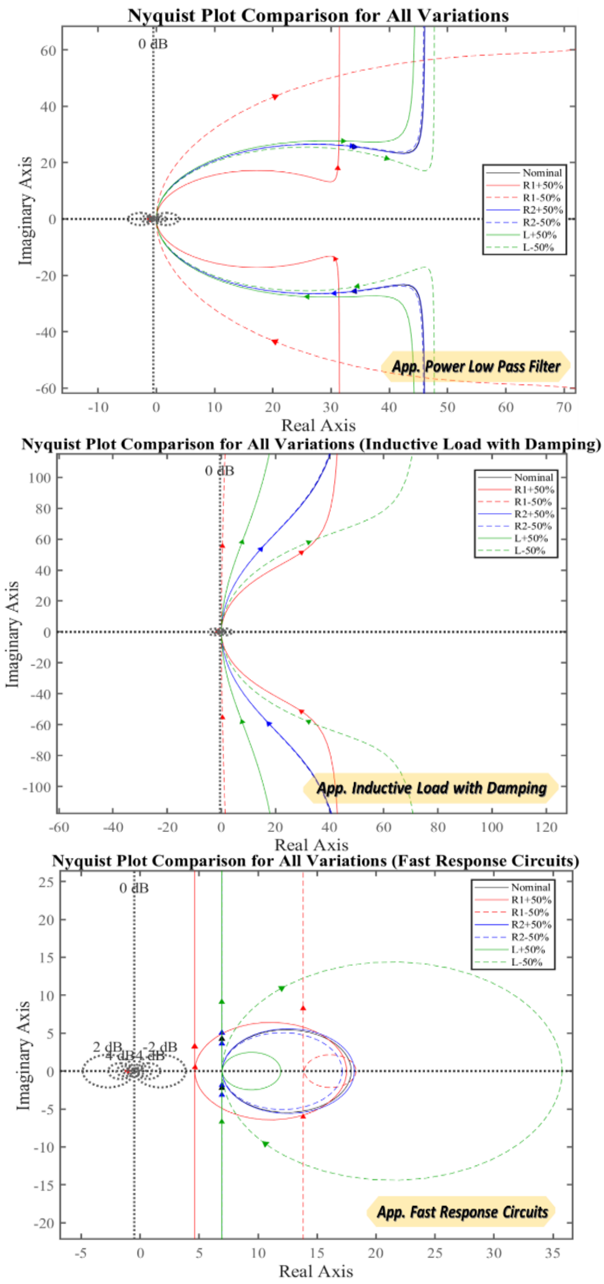

Figure 9. Nyquist plot comparison for all variations in RRL systems

3.5. Practical implementation considerations

Figures 11 and 12 analyze performance-computation trade-offs. While optimization requires initial investment (1.5-2.0 seconds for PSO), this one-time cost yields permanent benefits. Classical methods, though computationally trivial, produce persistently suboptimal performance. The weighted scoring system

(Figure 12) objectively favors PSO across multiple criteria. This systematic approach replaces subjective tuning with quantitative optimization, providing engineers with a reproducible methodology rather than artisanal guesswork.

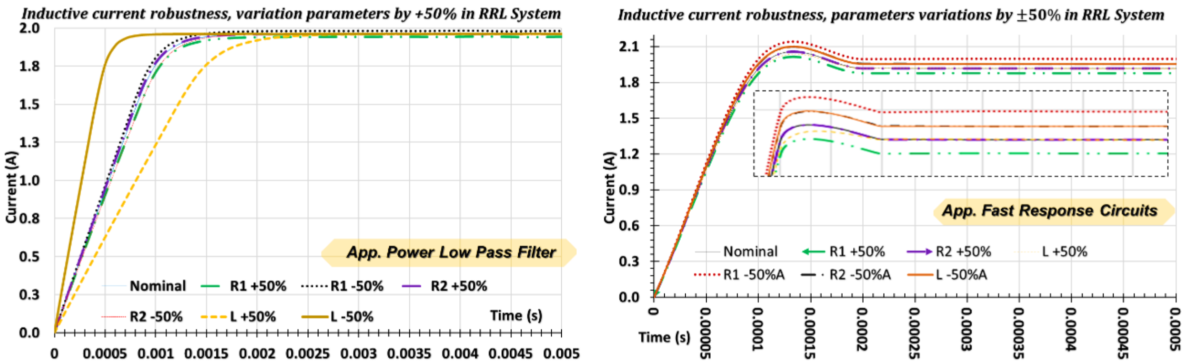

Figure 10. Inductive current robustness to parameters increased by +50% and decreased by -50%

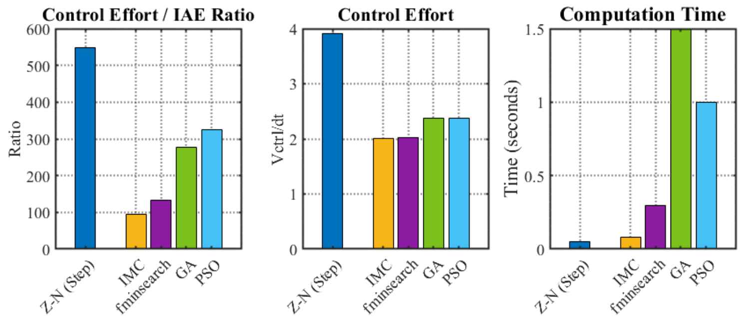

Figure 11. Performance vs computational cost analysis

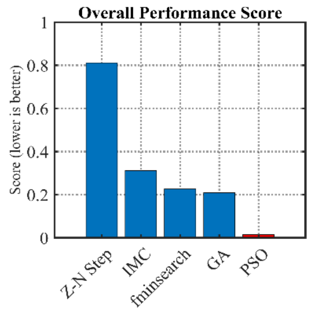

Figure 12. Overall performance score

3.6. Control effort and optimized gains

The control effort, measured as the integral of the squared control voltage V_{ctrl}^2, a critical factor for practical implementation is detailed in Table 8. These values are directly correlated with the optimized gain parameters, as higher gains typically demand more aggressive and energetically costly control actions. Analyzing this trade-off between performance and effort was essential for selecting the final controller tuning used in the hardware experiments. Consequently, the chosen gains reflect a deliberate balance, ensuring robust disturbance rejection while maintaining the control voltage within the actuator's physical saturation limits.

3.7. Robustness analysis of the optimal controller

The controller tuned via PSO was selected for a series of robustness tests to validate its performance under non-ideal, real-world conditions. While the conservative IMC method is the most energy-efficient, the optimized controllers maintain a reasonable control effort, especially given their vastly superior tracking performance. The final PID gains found by the optimization algorithms are listed in Table 9.

Table 8. Control effort ($\int V_{ctrl}^2\, dt$) across all methods and scenarios

Methods	Power low-pass filter	Inductive load with damping	Fast response circuits
Ziegler-Nichols	3.91	2.37	33.5
Genetic algorithm	2.33	1.93	9.22
Particle swarm	2.37	1.97	9.51

Table 9. Optimized PID gains K_p, K_i, K_d obtained from optimization algorithms

Methods	Power low-pass filter	Inductive load with damping	Fast response circuits
F_min.search	1.1, 74.3, 3.59E-4	5.65, 46.75, 3.13E-4	2.52, 9162, 1.10E-5
Genetic algorithm	9.69, 98, 3.11E-3	15.98, 104.21, 1.13E-3	35.5, 150, 1.85E-4
Particle swarm	49.3, 305, 1.03E-4	16.9, 127.2, 1.0E-5	49.8, 427, 1.0E-5

3.8. Key insights and implications

Three fundamental insights emerge. First, optimization superiority is conditional: excellent for moderate-to-slow systems but problematic for ultra-fast dynamics where IMC excels. Second, algorithms intelligently simplify structures, discovering PI controllers where derivative action adds only complexity. Third, robustness exceeds practical requirements, enabling deployment in real-world conditions with inherent uncertainties. Practically, this research provides clear guidelines: use PSO for new designs with time constants >1 ms, re-optimize existing systems for immediate improvements, and select IMC for ultra-fast applications. The discovered PI structures reduce implementation complexity while maintaining performance.

3.9. Limitations and future directions

While comprehensive, this simulation-based study requires hardware validation. Future work should explore real-time adaptive optimization, fractional-order PID extensions, and more complex circuit topologies. The automatic structure simplification suggests fundamental questions about optimal controller complexity that warrant deeper investigation. The framework establishes optimization as a systematic alternative to heuristic tuning, moving PID design from art to engineering science while maintaining practical applicability across diverse industrial scenarios.

4. CONCLUSION

This research demonstrates that optimization-based tuning, specifically using particle swarm optimization (PSO), offers a superior alternative to classical methods for controlling inductive loads and power filters. The proposed approach successfully resolves the traditional trade-off between response speed and stability, yielding controllers that significantly improve tracking accuracy while eliminating overshoot. A key finding of this study is the algorithm's capability to identify reduced-order PI structures as optimal for these applications, thereby minimizing implementation complexity without compromising performance.

Robustness analysis further validates the method, proving that the optimized controllers maintain stability despite significant parameter variations and external disturbances. However, the study establishes a critical boundary for method selection: while optimization strategies excel for systems with standard time constants, Internal Model Control remains the preferred approach for ultra-fast dynamics. Consequently, this work proposes a systematic, context-aware framework for controller design that replaces subjective tuning with a rigorous engineering methodology. These advancements provide a reliable foundation for enhancing industrial efficiency and product quality, paving the way for future research into real-time adaptive optimization techniques.

FUNDING INFORMATION

The authors received no financial support for the research, authorship, and publication.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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