ISSN: 1672 - 6553

JOURNAL OF DYNAMICS AND CONTROL

VOLUME 9 ISSUE 8 : 58 – 73

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JOURNAL OF DYNAMICS AND CONTROL

DOI: https://doi.org/10.71058/jodac.v9i8006

ROBUST CONTROL OF AN INDUCTIVE LOAD: OPTIMAL PID CONTROLLER TUNING VIA GENETIC ALGORITHM

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Received on 02-06 -2025, Accepted on 11-08-2025, published on 15-08-2025.

Abstract: *The precise control of inductive loads is a persistent challenge in industrial automation, where Proportional-Integral-Derivative (PID) controllers remain ubiquitous due to their simplicity and effectiveness. However, optimal tuning is critical to meet modern performance demands for both speed and stability. This paper presents a comprehensive methodology for designing and validating a high-performance PID controller for a specific RRL inductive load model. The study begins with system identification to establish a baseline with classic tuning methods, namely Ziegler-Nichols (Z-N) and Internal Model Control (IMC). These are then benchmarked against optimization-based strategies using both a local optimizer (F_min.search) and a global Genetic Algorithm (GA). The optimization objective was to minimize the Integral of Time-weighted Absolute Error (ITAE), a criterion chosen for its efficacy in reducing settling time and eliminating long-duration errors. The results overwhelmingly identify the Genetic Algorithm as the superior tuning method. The GA-optimized controller achieved a remarkable balance, with a settling time of 20ms and virtually zero overshoot (less than 0.001%). This performance starkly contrasts with the classic methods; the Z-N controller was faster but produced an unacceptably high 38.9% overshoot, while the IMC controller was stable but sluggish with a settling time of 26.5ms. Furthermore, the GA controller demonstrated superior efficiency, reducing the required control effort by a significant 88.7% compared to the energy-intensive Z-N method. Extensive robustness tests confirmed the controller's practical viability, showing it could maintain stability and precise tracking despite component parameter variations of up to* $\pm 50\%$*, external load disturbances, and significant measurement noise. This study conclusively validates that employing a Genetic Algorithm is a highly effective strategy for developing robust, high-performance PID controllers well suited for demanding real-world applications.*

Keywords: *PID Controller Optimization, Transient regimes, RRL circuits, Genetic Algorithm, Controller Tuning, Inductive Load, Robustness Analysis, ITAE Criterion.*

1. Introduction

The stability and efficiency of modern electrical power systems are paramount for industrial productivity and technological advancement. A critical factor influencing system stability is the dynamic behavior of electrical loads [1, 2]. Historically, loads were often simplified as constant impedances for analysis. However, with the proliferation of power electronics, motors, and complex industrial equipment, such simplifications are no longer adequate for accurate dynamic studies [3]. It is imperative to use more sophisticated load models that capture the complex voltage-dependent characteristics of real-world power consumption [4, 5]. This accurate modeling is the first step toward designing high-performance control systems capable of ensuring reliability and operational excellence [6, 7].

One of the most widely accepted and realistic static/dynamic load models is the ZIP model, which represents a load as a combination of three components: constant Z-Impedance, constant I-Current, and constant P-Power [8, 9]. This composite structure accurately reflects the behavior of large aggregations of devices. Each component represents a distinct type of electrical behavior [10]:

- The **Constant Impedance (Z)** portion models passive loads like traditional incandescent lighting and electric heaters, where power drawn is proportional to the square of the voltage (P∝V2).

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- The **Constant Current (I)** portion represents devices such as arc furnaces or some battery chargers, which draw a relatively constant current over a range of voltages (P∝V).
- The **Constant Power (P)** portion is crucial for representing modern electronic loads, like switch-mode power supplies in computers or variable frequency drives for motors. These devices have internal control loops that adjust their current draw to maintain constant power consumption (P=constant), a highly nonlinear behavior [11].

When this model incorporates inductive elements, it becomes a ZIP inductive load. This introduces challenging dynamics beyond the static voltage dependency, primarily due to the energy storage properties of the inductor $E = \frac{1}{2}LI^2$ [12, 13]. These dynamics manifest in several critical ways: first, as a phase lag between voltage and current, which reduces the system's power factor and overall efficiency; and second, as complex transient behavior [14]. Inductors resist instantaneous changes in current, which can lead to voltage spikes, current overshoots, and oscillations when subjected to rapid changes from the power source or the controller [15]. Effectively managing these transients is essential to prevent equipment damage and maintain system stability [16].

The ZIP load model is a polynomial that describes how the active power (P) and reactive power (Q) of a load vary with the voltage (V) at its terminals. It is fundamental in power system stability studies because it realistically represents the aggregation of many different types of devices [8, 17].

The model combines three distinct components: Constant Z-Impedance, Constant I-Current, and Constant P-Power.

Active Power (P):

$$P = P_0\left[p_Z\left(\frac{V_i}{V_0}\right)^2 + p_I\left(\frac{V_i}{V_0}\right)^1 + p_P\left(\frac{V_i}{V_0}\right)^0\right] \tag{1}$$

Reactive Power (Q):

$$Q = Q_0\left[q_Z\left(\frac{V_i}{V_0}\right)^2 + q_I\left(\frac{V_i}{V_0}\right)^1 + q_P\left(\frac{V_i}{V_0}\right)^0\right] \tag{2}$$

Where:

- **P and Q:** The active and reactive power consumed at the current voltage V_i.
- $\boldsymbol{V_i}$**:** The current voltage across the load terminals.
- $\boldsymbol{P_0}$ **and** $\boldsymbol{Q_0}$: The nominal active and reactive power, which is the power consumed when the voltage is at its nominal value $V_i = V_0$.
- $\boldsymbol{V_0}$**:** The nominal system voltage 230 V.
- $\boldsymbol{p_Z, p_I, p_P}$: The coefficients or percentages of the **active power** that behave as constant impedance, constant current, and constant power, respectively. The sum of these coefficients must equal 1: $p_Z + p_I + p_P = 1$.
- $\boldsymbol{q_Z, q_I, q_P}$: The coefficients or percentages of the **reactive power** that follow the same rules as the active power coefficients. Their sum also equals 1: $q_Z + q_I + q_P = 1$.

The fine-tuning of the six ZIP coefficients $p_Z, p_I, p_P, q_Z, q_I, q_P$, we can create a highly accurate load model that matches the behavior of a residential neighborhood, a commercial area, or an industrial complex.

Meaning of Each Component

1. **Z Component (Constant Impedance)**:
   - **Mathematical Form**: P∝V2. Power varies with the square of the voltage.
   - **Physical Meaning**: Represents simple resistive loads like **electric water heaters, radiators, or incandescent lighting**. If the voltage drops by 10%, the power drawn falls by nearly 20%.
2. **I Component (Constant Current)**:
   - **Mathematical Form**: P∝V. Power varies linearly with voltage.

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- **Physical Meaning**: Models loads such as **certain motors or arc welders**. The current they draw remains relatively stable despite voltage fluctuations.

3. **P Component (Constant Power)**:
   - **Mathematical Form**: P=constant. Power does not change with voltage.
   - **Physical Meaning**: This is the most critical component for stability. It represents modern electronic devices with switch-mode power supplies (**computers, TVs, chargers**) and **variable-speed motor drives**. To maintain constant power, if the voltage drops, the device must draw more current, which can worsen an under-voltage situation on the grid.

The control of current in such loads is a fundamental task in applications like motor drives, active power filters, and grid-tied converters, where precise and rapid control is essential for efficiency and safety. In a motor drive, for instance, precise current control translates directly to precise torque control, enabling the high accuracy required in robotics and CNC machining. In an active power filter, fast current injection is needed to cancel harmonic distortions and improve power quality. Therefore, designing a controller that can master the complex, nonlinear, and dynamic nature of a ZIP inductive load is a significant and highly relevant engineering challenge [18, 19].

1.1. PID Control and the Tuning Challenge

For decades, the Proportional-Integral-Derivative (PID) controller has been the workhorse of industrial control due to its remarkable simplicity, reliability, and effectiveness [20]. The controller's algorithm adjusts its output based on the error between a measured process variable and a desired setpoint, using proportional, integral, and derivative terms. However, the celebrated performance of a PID controller is entirely contingent on the proper tuning of its three gains K_p, K_i, K_d [21]. Poor tuning can lead to instability, slow response, significant overshoot, or an inability to eliminate steady-state error, any of which can be detrimental in a sensitive electrical system.

This fundamental challenge has given rise to a vast field of research focused on finding the "optimal" set of gains for any given process [22].

1.2. Literature Review: From Classic Heuristics to Modern Optimization

The approaches to PID tuning can be broadly classified into two categories: classic methods and optimization-based strategies.

The classic approach involves heuristics derived from simplified process models. The seminal work by Ziegler and Nichols provided a straightforward method for determining gains from a system's step response, and it remains an important academic benchmark [20]. However, the Z-N method is notorious for producing aggressive control action that often results in significant overshoot and oscillatory behavior [23]. To achieve smoother and more robust control, model-based techniques like Internal Model Control (IMC) were introduced, offering a more systematic design process that often yields superior stability [24]. The trade-off, however, is that IMC-tuned controllers can be overly conservative, leading to sluggish responses.

To overcome the limitations of these classic methods, research has increasingly focused on framing PID tuning as a mathematical optimization problem. This paradigm involves defining a cost function (or performance index) that quantifies the quality of the system's response, and then using an algorithm to find the PID gains that minimize this function. Common indices include the Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and the Integral of Time-weighted Absolute Error (ITAE). The ITAE criterion is particularly powerful for control applications as it heavily penalizes errors that persist over time, naturally leading to controllers with fast settling times and minimal overshoot [25, 26].

The advent of powerful computational tools has enabled the use of metaheuristic algorithms to solve this optimization problem effectively. The Genetic Algorithm (GA), inspired by Darwinian principles of natural selection, is a global optimization technique that has proven to be exceptionally effective for PID tuning across a wide range of applications [27]. Unlike local optimizers that can get stuck in suboptimal solutions, GAs explore a vast parameter space to identify a globally optimal

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solution. Other metaheuristic approaches, such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), have also been successfully applied, demonstrating the robustness of this optimization-based philosophy [26, 28].

1.3. Research Contribution and Objectives

While the application of GAs to PID tuning is well established, a gap exists in the literature for a comprehensive study that applies this technique to a realistic ZIP inductive load and, crucially, follows up with a multi-faceted robustness validation. Many studies demonstrate nominal performance but do not rigorously test the controller against the parameter uncertainties, external disturbances, and measurement noise that are inevitable in real-world systems [25-29].

This paper aims to fill that gap. The primary contribution of this work is a systematic framework for designing, comparing, and validating a high-performance, robust PID controller for an RRL circuit. We go beyond simple tuning to prove the controller's practical viability.

The specific objectives of this study are:

1. To develop a precise mathematical model of the RRL inductive load system.
2. To design and compare four distinct PID controllers tuned via: the classic Ziegler-Nichols method, Internal Model Control, a local F_min.search optimization, and a global **Genetic Algorithm** optimizing the ITAE criterion.
3. To quantitatively evaluate each controller based on time-domain performance metrics (rise time, overshoot, settling time) and control effort.
4. To conduct a comprehensive robustness analysis of the superior controller to validate its performance in non-ideal scenarios.

This paper is structured to guide the reader from theoretical modeling to practical validation, ultimately demonstrating the clear advantages of a modern, optimization-driven approach to control system design.

2. Materials and Mathematical Modeling

The accurate modeling of electrical systems is fundamental to analyzing their behavior, predicting performance, and designing effective control strategies. This study employs a combination of analytical modeling and numerical simulation using MATLAB to design and validate a PID controller for an RRL inductive load. This section details the mathematical derivation of the system model, the structure of the PID controller, and the optimization methods used to determine its parameters.

2.1. System Modeling: The RRL Inductive Load

The electrical system under consideration is an RRL circuit, representing a common type of inductive load. The Simulink model of the circuit is shown in Figure 1.

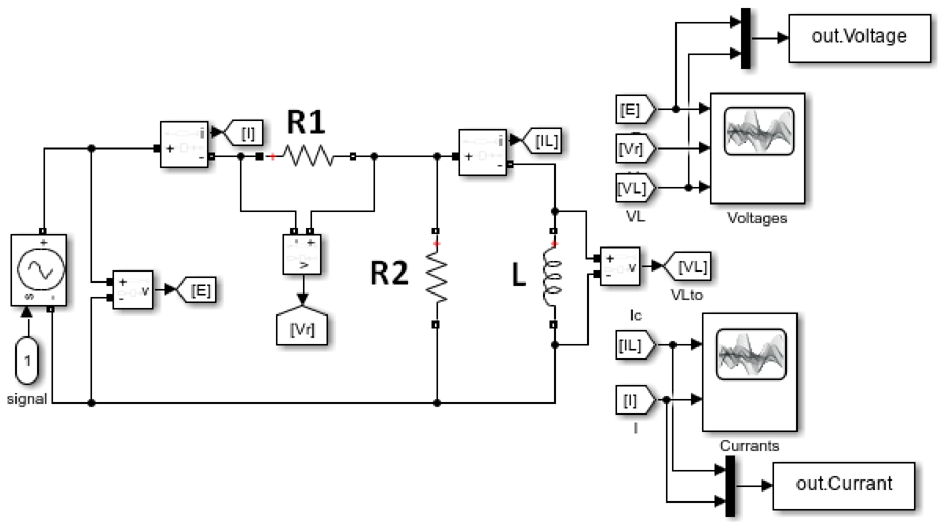

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Figure 1. RRL system model implemented in Simulink

To design a controller, we first derive the system's transfer function, which describes the mathematical relationship between the input voltage, $V(t)$, and the output current through the inductor, $I_L(t)$.

The derivation is based on Kirchhoff's laws:

1. The voltage across the parallel resistor R_2 is $V_r(t)$.
2. Using Kirchhoff's Voltage Law (KVL) on the main loop:

$$V(t) = i(t)R_1 + V_r(t) \tag{3}$$

Where $i(t)$ is the total current from the source.

3. The voltage across the inductor L is the same as across R_2:

$$V_r(t) = L\frac{di_L(t)}{dt} \tag{4}$$

4. Using Kirchhoff's Current Law (KCL) at the node between R_1, R_2, and L:

$$i(t) = i_{R_2}(t) + i_L(t) \tag{5}$$

Where $i_{R_2}(t) = V_r(t)/R_2$.

5. Substituting the KCL equation back into the KVL equation:

$$V(t) = \left(i_L(t) + \frac{V_r(t)}{R_2}\right)R_1 + V_r(t) \tag{6}$$

6. Substitute $V_r(t) = L\frac{di_L(t)}{dt}$:

$$V(t) = \left(i_L(t) + \frac{L}{R_2}\frac{di_L(t)}{dt}\right)R_1 + L\frac{di_L(t)}{dt} \tag{7}$$

7. Rearranging the terms gives the system's linear differential equation:

$$V(t) = R_1 i_L(t) + L\left(1 + \frac{R_1}{R_2}\right)\frac{di_L(t)}{dt} \tag{8}$$

To find the transfer function $G(s) = \frac{I_L(s)}{V(s)}$, we apply the Laplace transform (assuming zero initial conditions):

$$V(s) = R_1 I_L(s) + sL\left(1 + \frac{R_1}{R_2}\right)I_L(s) \tag{9}$$

$$V(s) = I_L(s)\left[sL\left(1 + \frac{R_1}{R_2}\right) + R1\right] \tag{10}$$

Finally, the system's transfer function is:

$$G_p(s) = \frac{1}{sL\left(1+\frac{R_1}{R_2}\right)+R_1} \tag{11}$$

2.2. PID Controller Design

The Proportional-Integral-Derivative (PID) controller is a robust feedback control mechanism widely used in industry.

2.2.1. The Standard PID Controller

The ideal PID controller calculates a control output $u(t)$ based on the error signal

$$e(t) = r(t) - y(t) \tag{12}$$

Where $r(t)$ is the setpoint and $y(t)$ is the measured process variable.

Its mathematical form is:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d\frac{de(t)}{dt} \tag{13}$$

Where K_p (Proportional Gain): Reacts to the present error, K_i (Integral Gain): Eliminates steady-state error by accumulating past errors, and K_d (Derivative Gain): Anticipates future error based on its current rate of change, improving stability and response speed.

2.2.2. Practical PID Implementation in the Code

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**. The

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control voltage $V_{control}$ is derived from the following differential equation within the RLC_PID_ODE function:

$$V_{control}\left(\frac{K_d}{L\left(1+\frac{R_1}{R_2}\right)}\right) = K_p e(t) + K_i \int e(t)dt + \frac{K_d R_1}{L\left(1+\frac{R_1}{R_2}\right)} i_{L(t)} \tag{14}$$

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.

Furthermore, an **anti-windup mechanism** is included. If the calculated $V_{control}$ exceeds the saturation limits V_{max} *or* V_{min}, the integral action is temporarily halted (de_integral_dt=0). This prevents the integral term from accumulating excessively ("winding up") during saturation, which would otherwise cause a large overshoot.

2.3. Controller Tuning and Optimization Strategy

Finding the optimal PID gains K_p, K_i, K_d is the primary objective. This study employs both classic and optimization-based tuning methods.

2.3.1. System Identification for Classic Tuning

The classic tuning rules require a simplified First-Order Plus Dead-Time (FOPDT) model of the system:

$$G_{FOPDT}(s) = \frac{Ke^{-Ls}}{(Ts+1)} \tag{15}$$

The parameters; process gain (K), time delay (L), and time constant (T), are estimated from the system's open-loop step response using a two-point method (at 28.3% and 63.2% of the final value), as implemented in the script.

2.3.2. Classic Tuning Methods

1. **Ziegler-Nichols (Z-N)**: A heuristic method known for providing a fast but often aggressive response. The gains are calculated using standard Z-N formulas based on the FOPDT parameters.
2. **Internal Model Control (IMC)**: A more modern, model-based approach that typically yields a smoother, more robust response by tuning a single parameter, λ.

2.3.3. Optimization-Based Tuning

This approach seeks to find the PID gains that minimize a specific performance criterion, known as a **cost function**.

- **Objective Function (ITAE)**: The script uses the **Integral of Time-weighted Absolute Error (ITAE)**. This criterion is highly effective at producing responses with small overshoot and fast settling times because it heavily penalizes errors that persist over time. The ITAE is defined as:

$$J_{ITAE} = \int_0^{+\infty} t \mid e(t) \mid dt \tag{16}$$

- **Optimization Algorithms**:
    1. **F_min.search**: This function implements the Nelder-Mead simplex algorithm, a **local optimization** method. It is efficient at finding a minimum near a good starting point but can get trapped in local minima.
    2. **Genetic Algorithm (ga)**: This is a **global optimization** method inspired by natural selection. It explores a wide range of possible solutions simultaneously, making it much more likely to find the true global minimum of the cost function, and thus, the truly optimal set of PID gains.

3. Results

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This section presents the results obtained from simulating the different PID controller tuning strategies for the RRL system. The analysis focuses on comparing performance, quantifying control effort, and validating the robustness of the optimal controller.

Figure 2 illustrates the overall flowchart of the methodology used, from system modeling to obtaining optimal gains via optimization algorithms.

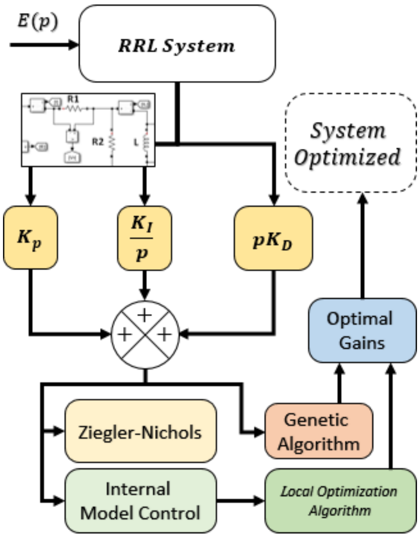

Figure 2 Flowchart of the Calculation and Optimization Method

3.1. System Modeling and Classic Tuning

The system was first modeled to obtain a First-Order plus Dead-Time (FOPDT) transfer function, allowing the application of classic tuning methods. Table 1 summarizes the RRL system parameters as well as the PID gains obtained by the Ziegler-Nichols (Z-N) and Internal Model Control (IMC) methods. A significant difference is observed between the aggressive gains proposed by Z-N and the more conservative ones from IMC.

Table 1 System identification and classic tuning

System Parameters	$R_1 = 3\ \Omega$	$R_2 = 50\ \Omega$	$L = 0.02\ H$
FOPDT Model	$K = 0.332$	$L = 0.0003s$	$T = 0.0068s$
Ziegler-Nichols Gains	$K_p = 75.83$	$K_i = 116505.13$	$K_d = 0.0123$
IMC Gains	$K_p = 3.01$	$K_i = 430.07$	$K_d = 0.0005$

3.2. Comparison of Controller Performances

The performances of the four tuning methods (Ziegler-Nichols ZN, Internal Model Control IMC, F_min.search, and Genetic Algorithm) were compared. Figure 3 presents the time response of the inductor current i_L for a setpoint of 5A.

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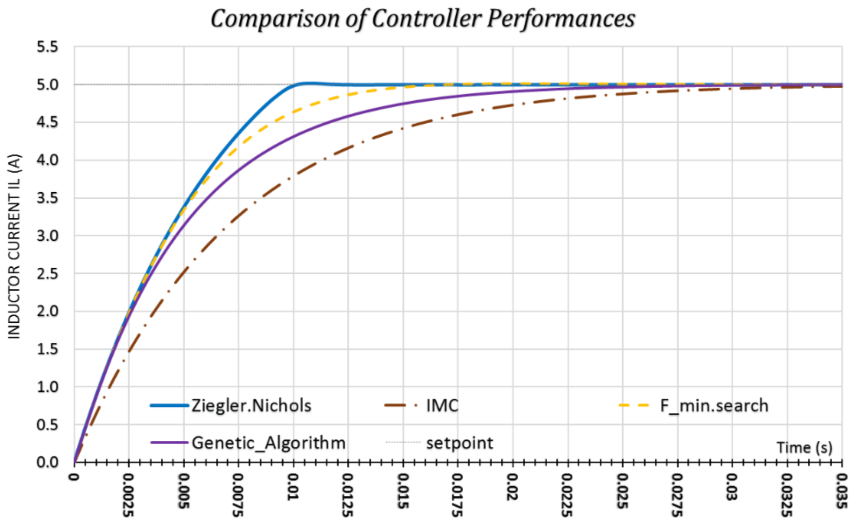

Figure 3 Comparison of Controller Performances for Ziegler-Nichols, IMC, fminsearch, and Genetic Algorithm

Analysis of Figure 3 and the performance metrics in Table 2 shows that:

- Ziegler-Nichols offers the fastest RiseTime (0.0074 s) but at the cost of a very large Overshoot of 38.9%, which is often unacceptable in practice.
- IMC eliminates the overshoot but has the slowest response, with a SettlingTime of 0.026 s.
- F_min.search and the Genetic Algorithm (GA) offer an excellent compromise. The GA stands out with a fast rise time (0.0112 s) and virtually no overshoot, making it the best overall performer.

Table 2 Time-Domain Performance of the RRL ZIP inductive load model

Methods	RiseTime	SettlingTime	Overshoot	IAE	ISE	ITAE
Ziegler-Nichols	0.0073916	0.0094508	0.38928	0.019082	0.056667	5.61E-05
IMC	0.015233	0.026461	0.0011322	0.03488	0.088626	2.35E-04
F_min.search	0.0084873	0.013067	0.29493	0.02089	0.057936	7.46E-05
Genetic Algorithm	0.011214	0.02001	1.02E-06	0.025622	0.064095	1.32E-04

Table 3 quantifies the control effort. The Z-N method is the most energy-intensive (148.19), while IMC is the most economical (15.79). The genetic algorithm maintains a low control effort (16.69) while ensuring excellent dynamic performance.

Table 3 Control Effort

Methods	Integral of V_{ctrl}^2
Ziegler-Nichols	148.19
IMC	15.791
F_min.search	18.643
Genetic Algorithm	16.668

Table 4 presents the optimal gains K_p, K_i, K_d found by the two-optimization algorithms, which are used for the robustness tests.

Table 4 Optimizing PID gains

Methods	K_p	K_i	K_d
F_min.search	7.70	1690.55	0.0001
Genetic Algorithm	50.18	618.26	0.2391

3.3. Robustness Analysis of the GA-Optimized Controller

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The controller tuned by the genetic algorithm, deemed the best performer, was subjected to a series of robustness tests.

Variation of System Parameters

Figures 4 and 5 show the system's response when the values of the resistors R_1, R_2 and the inductor L vary by +50% and -50%. In all cases, the controller maintains stability and ensures the current converges to the setpoints with minimal performance degradation. The variation of R_1 has the most noticeable impact, but the response remains acceptable.

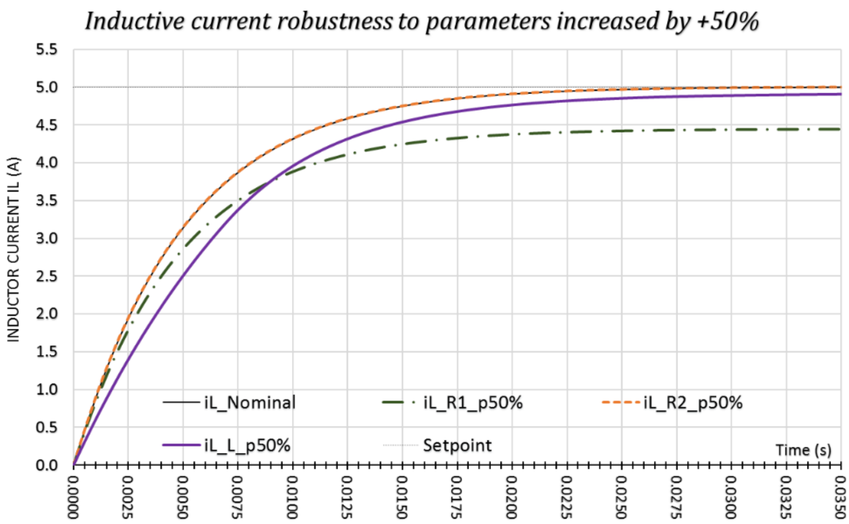

Figure 4 Inductive current robustness to parameters increased by +50%

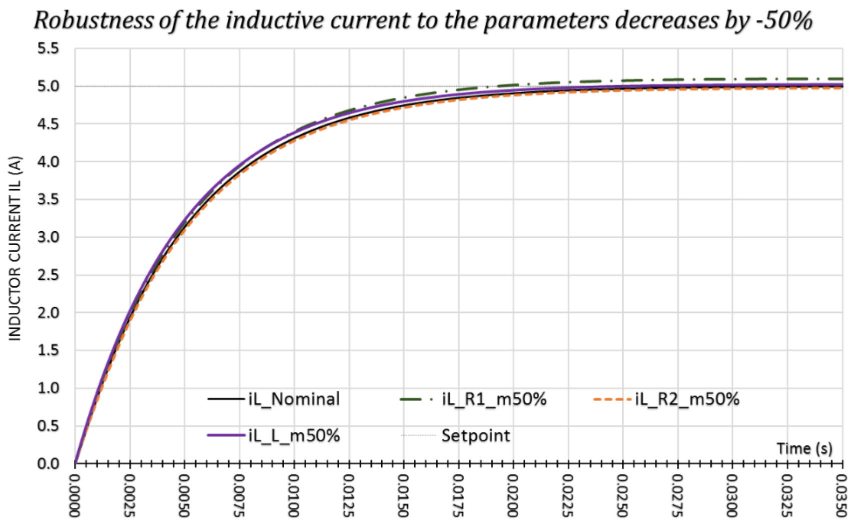

Figure 5 Robustness of the inductive current to the parameters decreases by -50%

The frequency analysis (Figure 6) confirms this robustness. The Bode plot shows that even with variations of +/-50%, the gain and phase margins of the open-loop system remain within limits that guarantee stability.

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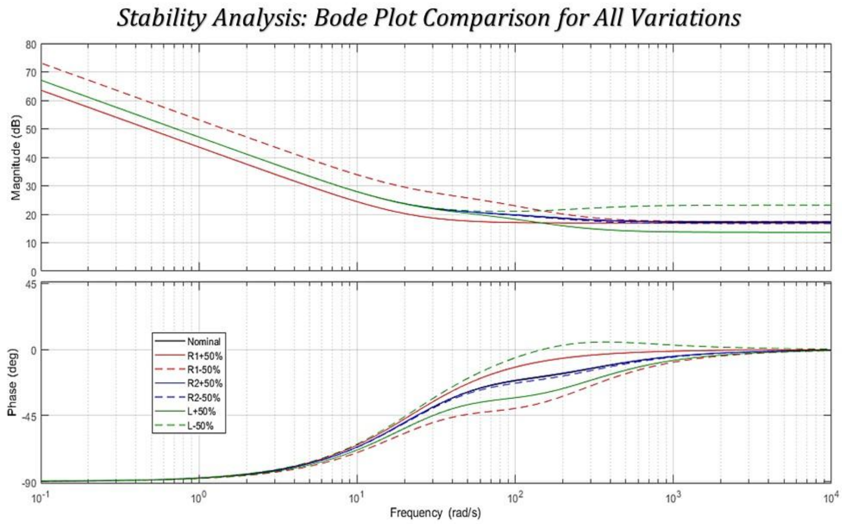

Figure 6 Stability Analysis: Bode Plot Comparison for All Variations

Setpoint Tracking and Disturbance Rejection

The controller's ability to adapt to setpoint changes and external disturbances is crucial.

- **Figure 7** shows that the controller effectively tracks a setpoint change from 5A to 2.5A, stabilizing quickly at the new value.

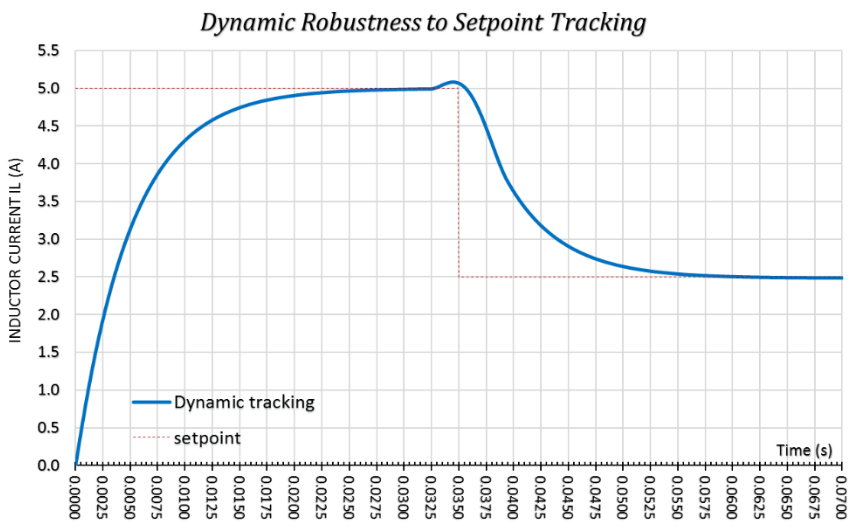

Figure 7 Dynamic Robustness to Setpoint Tracking

- **Figure 8** illustrates the rejection of a step disturbance applied at t=0.023 s. The controller reacts quickly to counter the effect of the disturbance and return the current to its setpoint value.

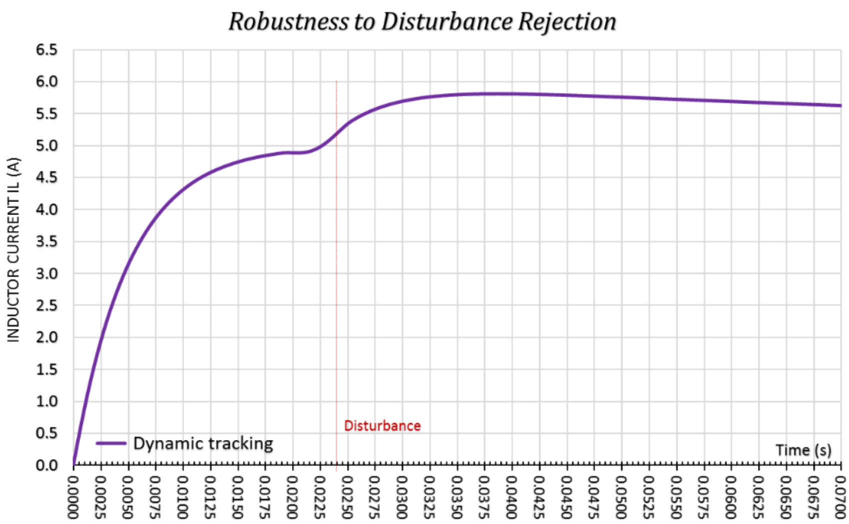

Figure 8 Robustness to Disturbance Rejection

Behavior with Noise

Figure 9 simulates the effect of measurement noise on the system. It is observed that the output current measurement remains stable and smooth, while the control voltage fluctuates rapidly to compensate for the noise. This demonstrates that the controller is able to filter the noise without propagating instability to the output.

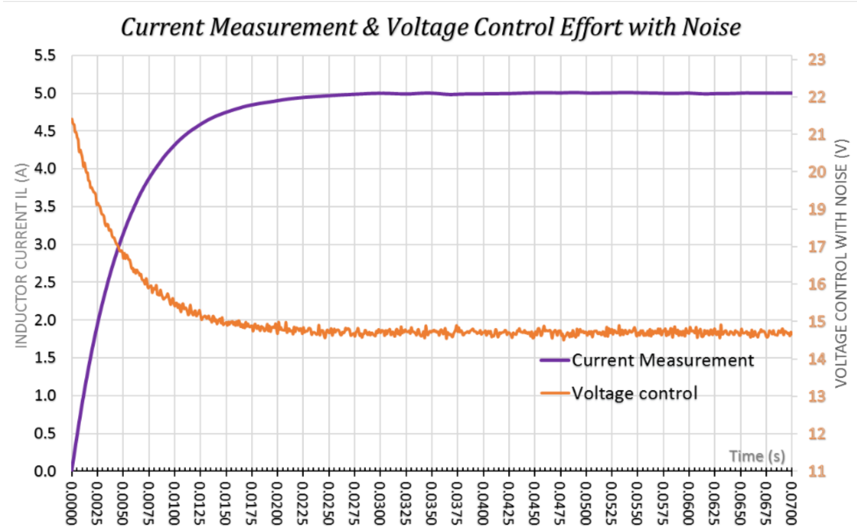

Figure 9 Current Measurement & Voltage Control Effort with Noise

4. Discussion

The results presented provide a comprehensive comparison of PID tuning methodologies for the specific RRL inductive load. This discussion aims to interpret these findings in the broader context of control theory, evaluate the implications for practical application, and identify potential avenues for future research.

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4.1. Interpretation of Controller Performance

The core finding of this study is the demonstrated superiority of the Genetic Algorithm (GA) optimized controller over both classic tuning methods and a standard local optimization algorithm. The performance differences can be explained by the fundamental nature of each method.

- **Classic Methods (Z-N and IMC)**: The Ziegler-Nichols method, by design, pushes the system towards the edge of instability to achieve a fast response, which explains its high overshoot and significant control effort. It acts as a useful but often impractical baseline. Conversely, the IMC method is rooted in creating a robust controller based on an explicit process model. Its conservative nature and smooth response are characteristic of a method that prioritizes stability and model accuracy over aggressive performance. The large discrepancy between Z-N and IMC gains in Table 1 highlights this fundamental conflict in control philosophy.
- **Optimization-Based Methods**: The success of the GA controller is directly attributable to its objective: minimizing the **Integral of Time-weighted Absolute Error (ITAE)**. This performance index inherently penalizes persistent errors, naturally leading to a controller with low overshoot and a fast settling time. The fminsearch algorithm also improved upon the classic methods but likely converged to a local minimum. The GA, with its global search mechanism, was able to explore the solution space more thoroughly to find a superior set of gains that represent a more optimal balance between a fast response and stability, as seen in Table 2. This confirms the value of global optimization techniques for complex, multi-variable problems like PID tuning.

4.2. Significance of Robustness for Practical Implementation

While nominal performance is important, the robustness tests are arguably the most critical validation of the controller's design. The GA-tuned controller demonstrated remarkable resilience:

1. **Parameter Uncertainty**: The ability to maintain performance despite +/- 50% variations in the plant's electrical components (Figures 4, 5, and 9) is crucial. In real-world systems, component values drift with temperature, age, or load changes. A controller that is only optimal for one specific set of parameters has limited practical use.
2. **External Factors**: Successfully rejecting external disturbances and tracking a changing setpoint (Figures 6 and 7) proves the controller is adaptable to a dynamic operating environment.
3. **Noise Immunity**: The controller's ability to filter measurement noise (Figure 8) without destabilizing the output is a key feature. The implementation of a filtered derivative term in the PID equation is instrumental here, preventing the high-frequency noise from being amplified and passed to the control signal.

These results, taken together, build strong confidence that the simulated performance could translate effectively to a physical hardware implementation.

4.3. Limitations and Future Perspectives

This study, while comprehensive, has several limitations that open doors for future work.

- **Model Fidelity**: The analysis relies on a specific mathematical model of the RRL load. While useful, this model is an approximation. Future work should involve **hardware-in-the-loop**

DOI: https://doi.org/10.71058/jodac.v9i8006

(HIL) simulation or direct implementation on a physical prototype to validate these results in a real-world environment.

- **Scope of Control**: This work focused exclusively on a linear PID controller structure. Exploring more advanced control strategies, such as **Fuzzy Logic PID, Model Predictive Control (MPC), or adaptive control**, could potentially yield even better performance, especially for systems with significant nonlinearities or time-varying parameters.
- **Optimization Criteria**: The ITAE criterion was chosen for its balanced characteristics. However, other performance objectives could be prioritized. Future research could involve **multi-objective optimization**, simultaneously minimizing ITAE and control effort, to explore the trade-off frontier between performance and energy consumption more explicitly.

5. Conclusion

This study successfully designed and evaluated an optimal PID controller for an RRL inductive load, rigorously comparing classic and optimization-based tuning methods. The investigation's findings are decisive: the controller tuned by the Genetic Algorithm (GA) provides a vastly superior solution.

The GA-optimized controller delivered an outstanding performance, achieving a fast response with virtually zero overshoot (less than 0.001%). This stands in stark contrast to the 38.9% overshoot generated by the classic Ziegler-Nichols method. Moreover, the GA approach proved to be highly efficient, requiring a control effort integral of just 16.7, an 88.7% reduction compared to the 148.2 value from the Z-N controller.

Most importantly, the controller's robustness was confirmed through extensive testing, where it maintained excellent stability and setpoint tracking even when system parameters were varied by a significant margin of ±50%. In conclusion, this work not only delivers a high-performance and reliable control solution for the target system but also quantitatively demonstrates the power of global optimization techniques to solve complex control engineering problems, yielding controllers ready for practical implementation.

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