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ADAPTIVE NEURO-FUZZY OPTIMIZATION OF PID CONTROLLERS WITH DIGITAL TWIN INTEGRATION FOR DYNAMIC SYSTEMS

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Abstract: *This paper proposes a practical framework for improving the performance of PID controllers. The core novel is the consideration of the digital twin of the controlled system in the fine-tuning process of the PID regulator, with adaptive neuro-fuzzy inference algorithms (ANFIS). The method is based on real-time feedback to adjust in a dynamic manner PID parameters, addressing challenges of nonlinear behaviors. Contributions include a customized ANFIS architecture, an optimization-specific cost function, and a feedback loop linking intelligent control strategies with system modeling. A case study on temperature regulation in 3D printing systems demonstrates reduced overshoot, faster stabilization, and elimination of steady-state errors, with improved energy efficiency. Comparative analysis confirms the method's superiority over conventional techniques and evolutionary advanced algorithms. This research advances adaptive control systems, providing robust solutions for dynamic and nonlinear systems.*

Keywords: *PID optimization, adaptive neuro-fuzzy inference system, dynamic system regulation, advanced control systems, intelligent control, 3D printer temperature control.*

1. INTRODUCTION

The Proportional-Integral-Derivative (PID) controller [1] is one of the most widely used control mechanisms in industrial and engineering systems due to its simplicity, robustness, and adaptability across a wide range of applications. However, the performance of PID controllers heavily depends on the precise tuning of their parameters, which can be challenging for nonlinear and dynamic systems [2, 3]. Traditional tuning methods often fail to address complexities such as system nonlinearity, environmental variability, and interaction among system components [4, 5, 6].

In response to these challenges, this paper introduces an innovative application of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [7] to dynamically optimize PID controllers within the context of digital twin simulations. Unlike traditional methods, such as Ziegler-Nichols tuning [8] or trial-and-error adjustments [9], which rely on static rules and are often limited in handling nonlinearities, this approach combines the adaptive learning capabilities of neural networks [10] with the rule-based decision-making of fuzzy logic [11]. By dynamically analyzing real-time system data, it efficiently adjusts PID parameters to account for complex nonlinear behaviors and uncertainties, such as varying environmental conditions, time-varying dynamics, and interacting control variables. This ensures precise regulation and stability even in highly dynamic systems, surpassing the reactive nature of conventional techniques. By integrating ANFIS with digital twin environments, the proposed framework provides a scalable and adaptive solution for achieving optimal performance in complex applications, as demonstrated in 3D printer temperature control.

The remainder of this paper is structured as follows: Section 2 reviews related work in PID optimization and ANFIS applications. Section 3 describes the proposed methodology, including integrating digital twins and optimization techniques. Section 4 presents the results of simulations, highlighting the performance improvements achieved. Finally, Section 5

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concludes with a discussion of the implications and potential future research directions.

2. LITERATURE REVIEW

2.1 Related work on PID optimization

The effectiveness of PID controllers largely depends on the precise tuning of the proportional, integral, and derivative gains, which can be challenging in nonlinear, complex, or time-varying systems [12]. Over the years, various approaches have been proposed to optimize PID parameters.

Classical methods like the Ziegler-Nichols [13] and Cohen-Coon [14] rules have been widely used for PID tuning. These methods rely on heuristic formulas derived from system step responses or open-loop data. While effective for linear systems, their limitations become apparent in nonlinear or multi-variable systems, often leading to overshoot, oscillations, or suboptimal performance [15].

The rise of computational intelligence has introduced metaheuristic algorithms for PID optimization. Evolutionary techniques such as Particle Swarm Optimization (PSO) [16], Genetic Algorithms (GA) [17], and Differential Evolution (DE) [18] have been employed to search for optimal PID parameters. These methods use global search strategies to minimize a cost function, often tailored to balance performance metrics like overshoot, settling time, and steady-state error. Although these approaches improve over traditional methods, they can be computationally expensive and lack adaptability to changing system dynamics.

Adaptive control strategies have been developed to address the dynamic nature of many industrial processes. Model Reference Adaptive Control (MRAC) [19] and Gain Scheduling [20] are examples of techniques that adjust PID parameters based on system behavior. However, these methods require precise models or predefined rules, limiting their applicability in highly uncertain environments.

Fuzzy logic [21] has been integrated into PID controllers to handle nonlinearities and uncertainties. By using linguistic rules and membership functions, fuzzy PID controllers dynamically adjust the control gains. While effective in managing uncertainties, these controllers depend heavily on the accuracy of the fuzzy rule base and membership functions, which can be challenging to design for complex systems.

The combination of neural networks and fuzzy logic, exemplified by Adaptive Neuro-Fuzzy Inference Systems (ANFIS), has gained attention for PID optimization. ANFIS leverages the learning capabilities of neural networks to automatically generate and refine fuzzy rules based on training data, offering a robust solution for dynamic and nonlinear systems [22].

Recent advancements in digital twin technology have enabled real-time modeling and simulation of physical systems [23]. Digital twins allow virtual experimentation and optimization before deployment when integrated with PID tuning. However, applying digital twins in conjunction with advanced intelligent control strategies, such as ANFIS, remains underexplored and presents a promising research direction.

2.2 ANFIS applications

ANFIS enables dynamic adjustments to nonlinear and uncertain systems. Notable applications include robotics, where ANFIS improves trajectory tracking and adaptive control [24]; HVAC systems, enhancing energy efficiency and maintaining precise environmental conditions [25]; and power systems, optimizing load balancing and fault detection [26]. These implementations demonstrate ANFIS's versatility and potential to outperform traditional control techniques, particularly in environments characterized by variability and uncertainty.

3. METHODOLOGY

3.1 Framework overview

The methodology proposed in this study integrates Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with digital twin technology to optimize PID controllers for dynamic system regulation. This framework addresses the challenges posed by nonlinearities, uncertainties, and time-varying behaviors in complex systems by leveraging intelligent control strategies and real-time system modeling.

A virtual representation of the target system provides a risk-free environment for simulating system dynamics and evaluating PID parameters. ANFIS dynamically adjusts the PID parameters by combining the learning capabilities of neural networks with the interpretability of fuzzy logic. A novel cost function is employed to optimize control parameters, ensuring robust performance across various operating conditions.

The digital twin serves as a virtual model of the physical system, accurately capturing its dynamic behavior. It is constructed using system identification techniques and real-world data. Key functionalities of the digital twin include:

- Simulation of nonlinear system dynamics under varying operational scenarios.
- Real-time feedback on system performance metrics.
- A safe environment for iterative tuning of PID parameters.

The ANFIS model is specifically tailored for PID tuning, with its architecture designed to enhance adaptability and precision. The model accepts error (e) and change in error (Δe) as inputs to reflect real-time system behavior. Adjusted PID gains (K_p, K_i, K_d) are generated dynamically. In addition, customized Gaussian membership functions are employed to handle nonlinearities and uncertainties. The digital twin provides comprehensive training data, covering various operational conditions and disturbances. The combination of neural network-based learning and fuzzy logic-based reasoning allows the ANFIS model to adjust PID gains in real time, ensuring optimal performance even in dynamic environments.

A cost function is introduced to evaluate the performance of PID controllers. The cost function is designed to balance four metrics (overshoot, settling time, steady-state error, and energy efficiency) using weighted objectives, enabling fine-grained optimization of control parameters. Dynamic weight adjustments further enhance the system's adaptability to changing conditions. Overshoot ensures minimal deviation from the desired output. Settling time reduces the time required for the system to stabilize. Steady-state error eliminates persistent discrepancies between the desired and actual output. Energy efficiency minimizes energy consumption during system operation.

The implementation process follows these steps:

- Develop the digital twin using system identification techniques.
- Use the digital twin to generate training and validation data.
- Train the ANFIS model with the generated data, refining membership functions and fuzzy rules.
- Employ the cost function to optimize PID parameters.
- Test the optimized PID controller within the digital twin under various scenarios.
- Apply the controller to the physical system and monitor real-world performance, using feedback to refine the model further.

3.2 Cost function

The cost function evaluates and optimizes the performance of PID controllers. In this paper, the cost function combines multiple performance indicators into a single objective function, enabling a comprehensive control quality assessment. The cost function is expressed as follows:

$$J = \omega_1 \cdot J_1 + \omega_2 \cdot J_2 + \omega_3 \cdot J_3 + \omega_4 \cdot J_4, \quad (1)$$

with $J_1 = \left(\frac{y_{max} - y_{desired}}{y_{desired}}\right)^2$, $J_2 = T_s$, $J_3 = \left|y_{steady} - y_{desired}\right|$, $J_4 = \int_0^T u(t)^2 dt$. Symbols ω_1, ω_2, ω_3, ω_4 are the weights of the main components of the cost function, J_1 is the component related to the overshoot O_s, J_2 is the component related to the settling time T_s, J_3 is the component associated to the steady-state error e_{ss}, and J_4 is the component linked to the energy efficiency E_c, $u(t)$is the control input signal, T is the operation duration, y_{steady} is the steady-state output, $y_{desired}$ is the desired output, and y_{max} is the maximum deviation of the system output from the desired setpoint.

A key innovation of this cost function is its dynamic weighting mechanism. The weights are adaptively adjusted based on system conditions or specific application requirements.

The proposed cost function is minimized using ANFIS, which dynamically adjusts the PID parameters to achieve the optimal trade-off among the performance metrics. The cost function is evaluated iteratively using data generated by the digital twin, ensuring a precise and adaptive optimization process.

The design of the novel cost function emerged from the need to address specific challenges in optimizing PID controllers for dynamic and nonlinear systems. Traditional cost functions often emphasize a limited set of performance metrics, such as overshoot or steady-state error, without adequately balancing competing objectives or considering the operational constraints of real-world applications. This realization leads to the creation of a comprehensive and adaptive cost function capable of addressing the unique demands of dynamic systems.

This multi-objective approach ensures a holistic system performance evaluation, making the cost function suitable for complex systems where trade-offs between metrics are unavoidable. A weighted approach is adopted to balance these competing objectives, with each term assigned an initial weight based on its importance to the application. To enhance adaptability, a dynamic weighting mechanism is introduced, allowing the relative importance of metrics to shift depending on the current operating phase of the system. For example, during transient states, higher priority is given to minimizing overshoot, while in steady-state operation, steady-state error and energy efficiency take precedence.

The digital twin plays an instrumental role in developing the cost function. By providing a virtual testing environment, the digital twin allows the system's behavior to be analyzed under various operating scenarios, including disturbances and nonlinearities. This iterative process informs the selection of terms in the cost function and their respective weights, ensuring a design tailored to real-world conditions. The cost function is designed to be modular and adaptable for broader applications. Its structure can accommodate additional metrics as needed for various applications, such as noise robustness in robotics or fault tolerance in power systems. The dynamic weighting mechanism further enhances its applicability across diverse dynamic systems, making it a versatile and innovative solution for PID optimization challenges.

3.3 Design algorithm for fuzzy logic rules

The effectiveness of the ANFIS-based PID controller depends significantly on the design of its fuzzy logic rules, which map input variables, such as error (e) and change in error (Δe), to output variables, including the proportional gain (K_p), integral gain (K_i), and derivative gain (K_d). This section outlines the systematic approach used to define, refine, and optimize the fuzzy logic rules.

Membership functions are chosen to represent the input variables (e and Δe) and capture system nonlinearities. Common choices include Gaussian and triangular membership functions, which provide smooth transitions. The number of membership functions is determined based on the system's complexity, typically ranging from 3 to 5 levels (e.g., Negative Large, Negative Small, Zero, Positive Small, Positive Large).

The fuzzy rule base is constructed as a set of "*IF-THEN*" rules to link input conditions to output actions. For example, we have *IF* e is Positive Small *AND* Δe is Zero, *THEN* K_p is Medium, K_i is Small, K_d is Small. These rules are initially designed based on an intuitive understanding of system dynamics. They provide a foundation for adaptive adjustments during training.

The initial rule base is refined using training data generated by the digital twin. ANFIS automatically adjusts the rule weights and membership function parameters during training, ensuring greater accuracy and adaptability. This step enhances the rules' effectiveness in dynamic and nonlinear environments. In systems with many input-output combinations, redundant or less-contributing rules are identified and pruned using optimization techniques such as genetic algorithms or feature selection. This step reduces computational complexity while maintaining system performance.

The number of fuzzy rules depends on the number of membership functions (M) for each input variable and the number of input variables

(N). The total number of rules is typically M^N. For instance, with 3 membership functions per input variable and 2 inputs, there will be $3^2=9$ rules. While a larger rule base provides finer control granularity, it increases computational overhead. The balance between rule base size and complexity is achieved through iterative training and validation.

A novel aspect of the methodology involves leveraging digital twin simulations to refine the rule base. The digital twin provides a controlled environment to test the initial rule set under various operating conditions. Poorly performing rules are flagged based on their contribution to the cost function improvement and frequency of activation during simulations. These rules are iteratively refined or eliminated, resulting in an optimized and efficient fuzzy rule set tailored to the system's dynamic behavior.

4. RESULTS

4.1 Case study

To validate the proposed methodology, a case study was conducted on the temperature regulation of a 3D printer head. This system presents significant challenges due to its nonlinear and dynamic behavior and the critical need for precise control to ensure print quality. The aim was to maintain a stable temperature during operation while minimizing energy consumption and ensuring rapid stabilization after disturbances.

The 3D printer head consists of a heating element controlled by a PID controller, responsible for maintaining the nozzle at a target temperature. Nonlinearities in the heat transfer dynamics and external disturbances, such as variations in ambient temperature or material feed rate, complicate the control task.

To account for the complexities of the 3D printer head heating system, including thermal inertia and additional heat sources, a second-order dynamic model is utilized. This model provides a more accurate representation of the system's behavior compared to a first-order approximation, particularly in capturing oscillatory and transient dynamics. The transfer function of the second-order system is expressed as:

$$G(s) = \frac{K}{\tau^2 \cdot s^2 + 2 \cdot \zeta \cdot \tau \cdot s + 1}, \tag{2}$$

with $G(s)$ the transfer function of the system, and K the system gain, representing the steady-state relationship between the input (power supplied) and the output (temperature), τ the dominant time constant, characterizing the speed of the system's response, and ζ the damping ratio, indicating the degree of oscillation in the system's response.

The damping ratio (ζ) determines the nature of the system's transient response. Values of $\zeta<1$ lead to underdamped responses with oscillations, $\zeta=1$ provides critically damped behavior, and $\zeta>1$ results in overdamped responses. The time constant (τ) defines the system's responsiveness; smaller values indicate faster responses, while larger values reflect slower dynamics.

The 3D printer head exhibits characteristics that justify using this second-order model. The heating element and surrounding material retain heat, introducing a lag in the system’s response to input power changes. Additional heat sources, such as ambient temperature fluctuations and heat conduction through materials, contribute to the system's complexity.

4.2 Digital twin modeling

The digital twin serves as a virtual replica of the 3D printer head heating system, providing a dynamic simulation platform to analyze and optimize the system’s behavior under various operating conditions. The modeling approach is based on a second-order system from the relationship (2) that captures the nonlinear and transient dynamics of the heating process, including thermal inertia and damping effects. The digital twin simulates a range of operating conditions by varying key parameters. The code for the simulation was written in Python, using the *numpy* and *matplotlib* libraries. Values of 3, 5, and 7 °C/W for K were tested to model different thermal efficiencies. Time constants τ of 5, 10, and 15 seconds were used to reflect different response speeds. Scenarios included underdamped (ζ=0.5), critically damped (ζ=1.0), and overdamped (ζ=1.5) cases.

The results, visualized in Fig. 1, illustrate how varying system gain and time constant impact the system's response. Higher *K* values result in a larger steady-state temperature, while larger τ values lead to slower responses.

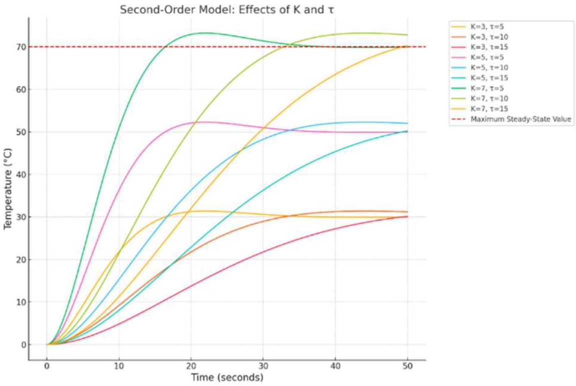

Fig. 1. Effects of system gain and time constant on temperature response in the second-order model.

Fig. 2 demonstrates the impact of the damping ratio on system behavior. Underdamped systems (ζ=0.5) exhibit oscillations before stabilizing, critically damped systems (ζ=1.0) achieve the fastest stabilization without oscillations, and overdamped systems (ζ=1.5) stabilize slowly with no oscillations.

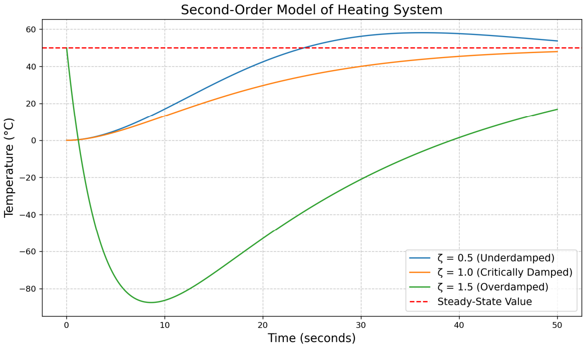

Fig. 2. Impact of damping ratio on temperature response in the second-order model.

The simulations revealed trade-offs between response speed, stability, and steady-state accuracy, informing the design of the control system. The simulated responses served as training data for the ANFIS-based PID controller, enabling precise parameter tuning and optimization.

The digital twin is built with key parameters (*K*, τ, ζ, and power input) that can be easily adjusted to represent different systems. The second-order system model can be reconfigured for systems with similar dynamic characteristics (e.g., heating, cooling, mechanical vibrations) by adapting the transfer function parameters without redesigning the entire model. The digital twin can simulate systems with varying complexity, from simple single-zone systems to multi-zone systems, by adding or removing components as needed. The Python-based simulation framework is designed to accommodate additional features (e.g., incorporating nonlinearities such as saturation effects, adding new inputs such as multi-zone heating or disturbances, and expanding to other system types, such as fluid flow or electrical systems).

4.3 Performance required for a 3D printer

The performance of a 3D printer is critically dependent on maintaining precise control over its dynamic systems, particularly in areas such as temperature regulation, motion control, and material handling (see Table 1). One of the primary performance requirements is minimizing overshoot, especially in temperature control systems for the printer's nozzle and bed. Overshoot must be kept below 5% to prevent overheating, which can lead to material degradation, nozzle clogging, or defects in the printed structure [27]. Maintaining stability during the transient response phase is essential to avoid system instability and ensure safe operation.

Achieving zero steady-state error is another crucial requirement. The nozzle temperature and positioning systems must precisely maintain the desired setpoint over extended periods, as even small deviations can compromise layer adhesion, dimensional accuracy, and the overall structural integrity of the print. This accuracy is particularly important for printing high-resolution or complex geometries. The settling time of the system must also be minimized, with a target of less than 10 seconds for temperature stabilization or motion adjustments [28]. Reducing delays ensures the printer can transition quickly between operational phases, such as heating to a new target temperature or repositioning the nozzle for the next layer. A shorter settling time improves productivity and reduces idle periods, especially in multi-stage printing processes. The rise time, typically required to fall within 5 to 10 seconds, is another critical performance parameter [29]. This ensures the system responds quickly enough to meet operational demands while avoiding abrupt changes that might destabilize the system. A balanced rise time supports speed and precision, allowing the printer to adapt to new conditions smoothly and without overshooting.

In addition to these key metrics, energy efficiency is an emerging priority for modern 3D printers, particularly in industrial or large-scale applications. Reducing energy consumption during heating and motion control enhances the sustainability of the printing process while lowering operational costs. Robustness against disturbances, such as variations in ambient conditions or material inconsistencies, is also vital to maintaining performance under real-world conditions.

Table 1 shows the key metrics that guide the optimization of the PID controller.

Table 1

Key performance parameters.

Metric	**Limit value**	**Reason**
Overshoot (%)	< 5%	Prevents spikes and ensures stability during transient responses.
Steady-state error	0.00	Ensures precise control, maintaining accurate temperature or position.
Settling time (s)	< 10 s	Minimizes delays, allowing the system to reach a steady state quickly.
Rise time (s)	$5 \text{ s} \leq T_r \leq 10 \text{ s}$	Balances speed and stability during the initial response phase.

4.4 PID optimization using ANFIS

The optimization of the PID controller for the heating bed of the nozzle in the 3D printer was achieved using an Adaptive Neuro-Fuzzy Inference System (ANFIS) model trained to dynamically adjust PID parameters (K_p, K_i, K_d) based on real-time feedback of system error and its rate of change. This approach leverages the adaptability of neural networks and the interpretability of fuzzy logic, enabling precise and robust control of dynamic systems.

The ANFIS model was implemented in Python with *numpy, tensorflow*, *scipy, pyswarm, skfuzzy,* and *matplotlib* libraries, using a neural network trained on a heuristic dataset generated through predefined fuzzy rules. Gaussian membership functions were used to represent fuzzy logic rules for input variables, error (e), and change in error (Δe). The membership functions included three states: Negative, Zero, and Positive. A condensed form of the fuzzy rules is shown in Table 2.

Table 2

A condensed form of the fuzzy rules.

IF e	**AND Δe**	**THEN K_p**	**THEN K_i**	**THEN K_d**
$e \neq 0$	$\Delta e \neq 0$	$K_p=2+0.1 \cdot e$	$K_i = 0.01 \cdot \lvert e \rvert$	e
$e \neq 0$	$\Delta e = 0$	$K_p=2+0.1 \cdot \mathrm{e}$	$K_i = 0.01 \cdot \lvert e \rvert$	e
$e=0$	$\Delta e \neq 0$	$K_p=2$	$K_i=0$	$K_d=0.2-0.01 \cdot \Delta e$
$e=0$	$\Delta e=0$	$K_p=2$	$K_i=0$	$K_d=0.2$

The ANFIS model was implemented and trained using a well-structured heuristic dataset derived from predefined fuzzy rules. This approach ensured that the training process was guided by expert knowledge and logical relationships, making it an effective method for initializing the model and ensuring its interpretability.

The predefined fuzzy rules were crafted based on domain expertise, capturing the fundamental dynamics of the system. These rules established relationships between the input variables - error (e) and change in error (Δe) - and the output PID parameters (K_p, K_i, K_d). Each rule reflected practical control objectives:

- Proportional gain (K_p) was adjusted based on the error magnitude to provide immediate correction.
- Integral gain (K_i) was scaled with the absolute error to eliminate steady-state error.
- Derivative gain (K_d) was adjusted inversely to the rate of change of error to mitigate oscillations.

The fuzzy rules were expressed mathematically, ensuring consistency and enabling systematic data generation. The training dataset was generated by applying the predefined fuzzy rules to a diverse range of errors and changes in error values. The heuristic dataset served as the foundation for training the

ANFIS model, consisting of a neural network architecture with two hidden layers (16 neurons each) to approximate the fuzzy mappings. The model was trained using the Mean Squared Error (MSE) loss function to minimize the difference between the predicted and actual values of K_p, K_i , and K_d. The training process leveraged 50 epochs and a batch size of 32 to ensure convergence without overfitting.

The ANFIS-based PID controller was evaluated using the digital twin with a setpoint of 50 units. The system response curve, as shown in Fig. 3, illustrates the dynamic behavior of the ANFIS-based PID controller. The response aligns closely with the setpoint throughout the simulation, with minimal overshoot and a rapid transition to steady-state conditions. The consistent tracking of the setpoint underscores the effectiveness of the ANFIS model in tuning the PID parameters dynamically.

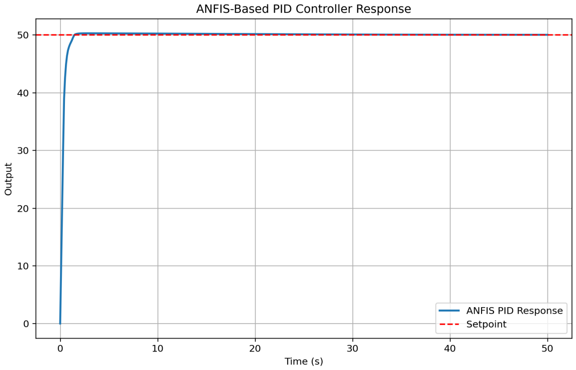

Fig. 3. Results of the optimized PID controller.

The system response metrics were computed to quantify its performance:

- The maximum overshoot observed was 0.53%, well below the recommended threshold of 5%, ensuring stability and precise transient control.
- The system achieved a steady-state error of 0.00, demonstrating the controller's ability to accurately reach and maintain the desired setpoint.
- The system's rise time was recorded at 0.70 seconds, reflecting a rapid initial response without compromising stability.
- The settling time was measured at 0.80 seconds, confirming the system's ability to stabilize quickly within the acceptable tolerance range.

5. DISCUSSION AND CONCLUSION

5.1 Comparative analysis

Fig. 4 illustrates the comparative analysis of various PID tuning methods, showcasing their differences in key metrics such as overshoot, steady-state error, rise time, and settling time across a dynamic system's temperature control response. Graphics have been generated by introducing the models of the compared algorithms into a Python script and running it in Jupyter Notebook.

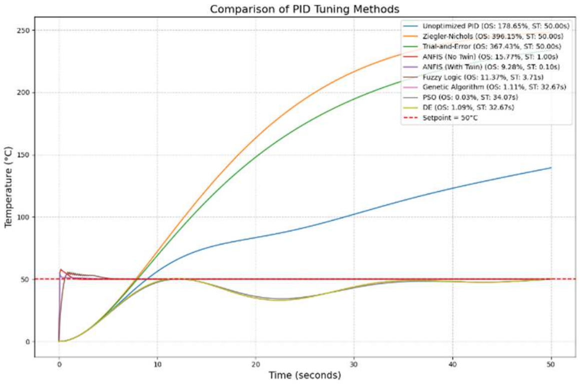

Fig. 4. Comparative analysis of the tunning methods.

Unoptimized PID tuning demonstrates the poorest performance, with excessively high overshoot and prolonged settling time, making it unsuitable for precise applications. The system's response remains unstable and sluggish, illustrating the necessity of structured tuning approaches.

Ziegler-Nichols and trial-and-error methods show similarly inadequate results, with both producing significant overshoot and slow stabilization. Although these techniques are widely used for their simplicity, their inability to handle nonlinearities and uncertainties renders them impractical for complex dynamic systems.

ANFIS without a digital twin marks a significant improvement over the classical methods. By incorporating neural and fuzzy logic techniques, it reduces overshoot and achieves rapid stabilization. However, while it addresses system nonlinearities better than traditional methods, its performance is still limited compared to more advanced approaches.

Fuzzy logic provides a robust solution for managing nonlinearities and uncertainties. Its performance is characterized by moderate overshoot and acceptable rise time, although its settling time is slightly longer than that of ANFIS with the digital twin. Nonetheless, it offers a balanced and effective control strategy for many dynamic systems.

Optimization algorithms such as genetic algorithms, particle swarm optimization, and differential evolution focus on minimizing overshoot and steady-state error. These techniques achieve near-perfect accuracy but tend to compromise on rise and settling times. The trade-off between precision and speed is evident in their slower stabilization compared to ANFIS-based methods.

The integration of a digital twin with ANFIS delivers outstanding results, with minimal overshoot, zero steady-state error, fast rise time, and exceptionally short settling time. This approach leverages the digital twin's real-time feedback and adaptability to optimize system performance dynamically, making it the most effective method among those analyzed.

Results related to the four key metrics achieved with each tunning method are synthetically shown in Table 3.

The comparative analysis highlights the significant advantages of intelligent control methods, particularly those enhanced by real-time digital twin integration.

By leveraging real-time data and high-fidelity system simulations, digital twins enable intelligent systems like ANFIS to dynamically adapt to nonlinearities, uncertainties, and time-varying behaviors, ensuring precise and efficient control.

While classical techniques fall short in handling system complexities due to their static nature and reliance on simplified models, advanced approaches such as ANFIS with a digital twin offer unparalleled adaptability and optimization. This integration improves performance metrics such as overshoot, settling time, and steady-state error and sets a benchmark for managing increasingly complex dynamic systems in diverse applications, from industrial automation to energy systems and beyond.

Table 3

Comparative table of performance metrics.

Method	Overshoot (%)	Steady-State Error	Rise Time (s)	Settling Time (s)
Unoptimized PID	178.65	0.00	50.00	50.00
Ziegler-Nichols	396.15	0.00	50.00	50.00
Trial-and-Error	367.43	0.00	50.00	50.00
ANFIS (No Twin)	15.77	0.00	0.70	1.00
Fuzzy Logic	11.37	0.00	0.70	3.71
Genetic Algorithm (GA)	1.11	0.00	29.00	32.67
Particle Swarm Optimization (PSO)	0.03	0.00	30.00	34.07
Differential Evolution (DE)	1.09	0.00	28.00	32.67
ANFIS (With Twin)	0.53	0.00	0.70	0.80

5.2 Conclusions and future research

This paper introduced a novel approach to PID controller optimization by integrating Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with digital twin technology, offering a dynamic and robust framework for addressing nonlinear and time-varying behaviors in complex systems. The methodology demonstrated its capability to systematically optimize control parameters by leveraging the digital twin for real-time feedback, allowing precise adjustments to dynamic conditions. This research contributes to intelligent control system design by proposing a modular, adaptable framework that can be extended to various industrial applications.

Future research should build on these findings to address several open areas. First, the scalability of the proposed method to multi-input multi-output (MIMO) systems should be explored, as most real-world systems involve interdependent dynamics.

Second, incorporating advanced digital twin technologies (e.g., leveraging real-time data integration, high-fidelity simulations, predictive capabilities, and autonomous decision-making) could further improve adaptability and optimization.

Third, the use of hybrid control strategies, such as combining ANFIS with model predictive control (MPC), may help achieve an optimal balance between precision and computational efficiency.

Additionally, research into adaptive cost functions, which evolve with the operating conditions or performance goals, could enhance the versatility of the optimization framework.

The integration of ANFIS with advanced digital twin technology opens exciting possibilities for applications in cutting-edge fields, such as adaptive robotics, precision medicine, and sustainable smart cities. As industries move toward Industry 5.0, this approach could serve as a cornerstone for creating systems that respond to changes and anticipate and adapt to future scenarios.

For the case of 3D printers, this research on ANFIS-based PID optimization with digital twin integration opens several avenues for future contributions that extend beyond temperature regulation and address broader challenges within the 3D printing ecosystem, The methodology could be applied to optimize filament extrusion processes, ensuring consistent flow rates and preventing issues such as clogging or under-extrusion. Real-time monitoring and adaptive control could improve layer consistency and print quality.

The integration of ANFIS with digital twins could enhance motion control systems by dynamically adjusting motor speeds, accelerations, and decelerations to minimize vibrations, reduce ringing artifacts, and improve dimensional accuracy.

Intelligent control systems could facilitate seamless transitions between different materials during a single print job, dynamically adjusting parameters such as nozzle temperature, extrusion rates, and cooling times to optimize for material properties.

The research framework could be extended to optimize energy consumption during printing by dynamically regulating heating and cooling systems based on the requirements of different print phases, leading to more sustainable 3D printing operations.

Digital twin integration could enable real-time error detection by comparing live data with the simulated model. This could facilitate automatic corrections to recover from print failures, such as warping, layer misalignment, or filament breakage. Digital twins could be also used to simulate and optimize post-processing steps such as annealing or surface finishing, ensuring consistent results across different batches.

The proposed methodology could be adapted to optimize printing parameters for advanced materials such as composites, conductive filaments, or bio-materials, addressing challenges like uneven heat distribution and curing times. The framework could be also scaled to manage fleets of 3D printers in industrial settings, optimizing workflows, resource allocation, and maintenance schedules for maximum efficiency.

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Optimizarea adaptivă neuro-fuzzy a controlerelor PID cu integrarea replicilor digitale pentru sisteme dinamice

Această lucrare propune un cadru practic pentru îmbunătățirea performanței regulatoarelor PID. Noutatea principală constă în utilizarea unui geamăn digital al sistemului controlat în procesul de ajustare fină a regulatorului PID, cu ajutorul algoritmilor adaptivi de inferență neuro-fuzzy (ANFIS). Metoda se bazează pe feedback în timp real pentru ajustarea dinamică a parametrilor PID, abordând provocările comportamentelor neliniare. Contribuțiile includ o arhitectură ANFIS personalizată, o funcție de cost specifică optimizării și un circuit de feedback care leagă strategiile inteligente de control cu modelarea sistemului. Un studiu de caz asupra reglării temperaturii în sistemele de imprimare 3D evidențiază reducerea suprareglajului, stabilizarea mai rapidă și eliminarea erorilor de stare permanente, cu o eficiență energetică îmbunătățită. Analiza comparativă confirmă superioritatea metodei față de tehnicile convenționale și algoritmii evolutivi avansați. Această cercetare aduce progrese în sistemele de control adaptativ, oferind soluții robuste pentru sisteme dinamice și neliniare.

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