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Application of Jaya Algorithm in Optimizing ANN-Based PID Controllers for Single Area Load Frequency Control

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Abstract: This research explores the implementation of Artificial Neural Network (ANN)-based controllers for single-area Load Frequency Control (LFC) in power systems. While Proportional-Integral-Derivative (PID) controllers are commonly utilized, their limitations in addressing dynamic and non-linear scenarios underscore the necessity for adaptive control approaches. This study evaluates the performance of conventional PID controllers, ANN-PID controllers, Jaya Algorithm-optimized PID controllers, and ANN-Jaya-PID controllers. MATLAB Simulink is used to simulate and implement various control strategies. The ANN model is trained using simulation-generated data to accurately predict controller behavior under fluctuating load conditions. The Jaya Algorithm is applied to optimize the PID parameters, thereby enhancing the controller's effectiveness in maintaining frequency stability. The results indicate that the ANN-Jaya-PID controller delivers superior performance compared to the other configurations, achieving faster settling times and reducing overshoot and undershoot during load disturbances. Furthermore, the Jaya optimization notably enhances the robustness of the LFC system, particularly in managing the non-linear characteristics of contemporary power grids.

Keywords: Artificial Neural Network, Load Frequency Control, Jaya Algorithm, PID controller

Abstract (Malay): *Kajian ini menyelidik penggunaan pengawal berasaskan Rangkaian Neural Buatan (Artificial Neural Network, ANN) untuk Kawalan Beban Frekuensi (Load Frequency Control, LFC) dalam sistem kuasa bagi kawasan tunggal. Pengawal Proportional-Integral-Derivative (PID) konvensional telah digunakan secara meluas, namun ia menghadapi kekangan apabila berhadapan dengan keadaan dinamik dan tidak linear, yang menunjukkan keperluan untuk strategi kawalan yang adaptif. Kajian ini menilai prestasi pengawal PID konvensional berbanding pengawal ANN-PID, PID yang dioptimumkan melalui Algoritma JAYA, serta pengawal ANN-JAYA-PID. Strategi kawalan yang berbeza ini dilaksanakan menggunakan perisian MATLAB Simulink. Model ANN dilatih berdasarkan data daripada simulasi sistem bagi memastikan ia dapat meramalkan tingkah laku pengawal dengan tepat dalam pelbagai keadaan beban. Algoritma JAYA digunakan untuk mengoptimumkan parameter PID, seterusnya meningkatkan keupayaan pengawal dalam mengekalkan kestabilan frekuensi. Hasil kajian menunjukkan bahawa pengawal ANN-JAYA-PID mengatasi konfigurasi lain dengan mencapai masa kestabilan yang paling pantas, disamping meminimumkan lonjakan dan penurunan dari nilai sasaran yang ditetapkan semasa berlaku gangguan beban. Selain itu, pengoptimuman menggunakan Algoritma JAYA secara signifikan meningkatkan keteguhan sistem LFC, terutamanya menghadapi cabaran ketidaklinearan yang wujud dalam rangkaian grid kuasa moden.*

Kata Kunci: *Rangkaian Neural Buatan, Kawalan Beban Frekuensi, JAYA Algorithm, Pengawal PID*

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1. Introduction

Maintaining nominal frequency and tie-line power is vital for ensuring continuous power delivery within power systems (Shrestha & Gonzalez-Longatt, 2021). Fluctuations in active power resulting from varying load demands affect system frequency, while reactive power predominantly impacts voltage magnitude. Controlling frequency deviations is essential to achieving load-generation balance and maintaining overall system stability. As the demand for efficient and reliable power system operations grows, accurate load frequency control (LFC) becomes increasingly critical for maintaining system frequency and power flow near nominal levels (Memane et al., 2018). Proportional-Integral-Derivative (PID) controllers are widely adopted in the industry due to their simplicity and ease of implementation (Anwar & Pan, 2013).

The integration of renewable energy sources (RES) into power grids has heightened the need for adaptive and efficient LFC mechanisms (Wang et al., 2019). Artificial intelligence (AI) techniques offer a promising solution to address this challenge. Among these, Artificial Neural Network (ANN)-based control has gained attention for its learning capabilities and ability to approximate complex functions. Additionally, researchers have explored Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and fuzzy logic-based controllers to manage the inherent non-linearities and complexities of LFC (Jood et al., 2019).

Although PID controllers are extensively utilized in power systems for LFC, their effectiveness is limited by several factors. A significant limitation is their sensitivity to parameter tuning, particularly in systems characterized by non-linearities and external disturbances (Saini & Ohri, 2023). Furthermore, PID controllers often struggle to maintain optimal performance under varying load conditions and system parameters, leading to substantial frequency deviations and prolonged settling times (Mohammed & Dodo, 2023). Simulation studies have shown that these controllers exhibit slower response times and larger overshoots when faced with abrupt load changes (Putra et al., 2023).

To overcome these challenges, advanced control strategies and optimization techniques have been developed. Nature-inspired algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Bat Algorithm (BA), have demonstrated their ability to enhance PID parameter tuning, thereby improving frequency stability and reducing overshoot. However, the increasing complexity and variability of modern power grids, driven by the growing penetration of RES like wind and solar power, present additional challenges. The reduced system inertia and heightened sensitivity to load and generation variations exacerbate issues related to frequency stability and voltage profiles (El-Sousy et al., 2023). One recent optimization technique, the JAYA algorithm, has shown promise in addressing these challenges. The JAYA algorithm, a gradient-free optimization method, iteratively refines candidate solutions by steering them toward the best solution while avoiding the worst. Its straightforward design and minimal control parameters make it an effective tool for solving various optimization problems, including LFC. When applied to LFC, the JAYA algorithm has demonstrated its ability to optimize control parameters, enhancing system stability and performance. Comparative studies indicate that the JAYA algorithm outperforms methods like PSO in certain scenarios, further highlighting its robustness and efficiency in power system applications (Qu et al., 2024).

Optimization using the Jaya algorithm has demonstrated superior efficacy in minimizing integral time-multiplied absolute error (ITAE) values, a critical metric for ensuring frequency stability and achieving faster convergence under varying load conditions (El-Sehiemy et al., 2023). The algorithm's robustness and precision are further underscored in its application to Automatic Generation Control (AGC) of interconnected power systems with diverse energy sources, where it surpasses other methodologies in terms of system settling time, overshoot, and undershoot performance metrics (Pahadasingh et al., 2022).

Fuzzy logic-based controllers have gained traction in Load Frequency Control (LFC) due to their capability to manage non-linearities and uncertainties. However, these controllers face notable challenges, particularly in the tuning of fuzzy rules and membership functions, which can become complex and time-intensive, especially in large-scale systems comprising multiple areas and energy sources (Shangguan et al., 2021). Similarly, Artificial Neural Network (ANN)-based control systems have exhibited significant advantages over traditional controllers, such as PID controllers, especially in terms of performance and adaptability. While PID controllers are valued for their simplicity and robustness, their fixed structure limits their effectiveness in addressing nonlinear systems, time-delayed linear systems, and time-varying systems (Efheij & Albagul, 2021).

ANNs can be categorized into two primary types feedforward and feedback networks distinguished by their structural mapping architectures. Among these, feedforward networks are the most prevalent in deep learning applications, owing to their foundational role and adaptability across a broad range of domains. Notably, the initialization of weights in feedforward networks has a substantial impact on training efficiency and performance, with critical line initialization demonstrating faster convergence rates and improved scalability (Cardona, 2023).

Despite their potential, ANN-based LFCs encounter significant challenges, particularly the complexity involved in training these models for multi-area power system networks (PSNs) characterized by substantial load demand variations. Addressing this complexity often requires advanced optimization methods, such as particle swarm optimization (PSO), to determine the optimal number of nodes and initialize neurons effectively, processes that can be computationally demanding and time-intensive (Al-Majidi et al., 2022).

Traditional PID controllers, on the other hand, necessitate meticulous parameter tuning, which becomes challenging in systems subject to frequent load changes and parameter variations (Saba et al., 2023). Conversely, optimal ANN-PID controllers offer a more dynamic solution by adapting to these variations in real-time. ANN models can learn and predict system behaviors, facilitating real-time optimization of PID parameters, which enhances the controller's robustness and overall performance. This adaptability is particularly crucial in interconnected power systems experiencing frequent load demand fluctuations. In this paper:

- The performance of traditional PID controllers is evaluated in comparison to advanced ANN-based controllers, with an emphasis on their effectiveness in handling load variations.

- The study explores the incorporation of JAYA optimization to enhance the tuning of PID parameters and to improve the ANN's ability to predict optimal controller responses under varying load conditions

The LFC is designed using an ANN-based technique, where the PID controller parameters are optimized with the Jaya Algorithm for a single-area power system. The training data for the ANN model are generated and analyzed from the proposed optimization process, as illustrated in Fig. 1.

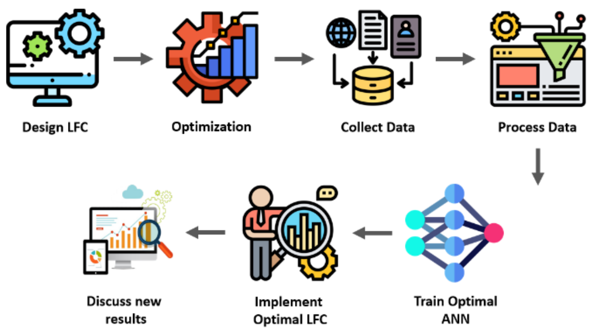

Figure 1: Work Strategy Process

2. System Background

2.1 Single Area LFC Model

Load Frequency Control (LFC) modelling plays a vital role in analyzing a power system's dynamic response to load fluctuations and disturbances. Its primary purpose is to maintain the balance between power supply and load demand, ensuring the system frequency remains within permissible limits. The LFC model accounts for the dynamic interactions between governors, turbines, and load behavior, while simplifying the analysis by disregarding nonlinearities for ease of implementation (Roca et al., 2022). Fig. 2 illustrates the single-area LFC model for a thermal power system.

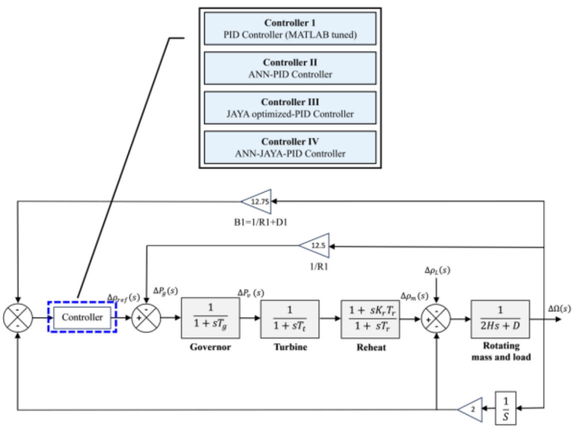

Figure 2: Single Area LFC Model For A Thermal Power System

In this study, various methods were employed to evaluate the performance of the proposed controller for the single-area load frequency control (LFC) model. The controllers assessed include a PID controller tuned using the MATLAB Tuner, an ANN-PID controller, a JAYA-optimized PID controller, and an ANN-JAYA-PID controller. These were analyzed in terms of maximum overshoot, maximum undershoot, and transient time during step load changes. System parameters were collected both before and after the controller block to train the ANN controller for Controller 2 and Controller 4, ensuring the ANN was trained using the tuned and optimized controllers simulated in Controller 1 and Controller 3. The parameters of the single-area model are detailed in Table 1.

Table 1: System Parameters LFC

LFC system parameters	Values
Generator power output, $\mathbf{P_{out}}$	250MW
System frequency, Hz	60 Hz
Speed regulation, R	15 pu
Governor time constant, $\mathbf{T_g}$	0.3 Sec
Turbine time constant, $\mathbf{T_t}$	0.5 Sec
Turbine reheat constant, $\mathbf{K_r}$	0.5 Sec
Turbine reheat time constant, $\mathbf{T_r}$	12 Sec
Inertia constant, H	5 Sec

2.2 System Controllers

This study utilizes a PID controller to optimize the Load Frequency Control (LFC) system. The controller adjusts the Area Control Error (ACE) by employing proportional, integral, and derivative components of the error signal. The ACE quantifies the deviation between the system's desired and actual outputs. The proportional component addresses the current error, the integral component accumulates past errors to eliminate steady-state discrepancies, and the derivative component anticipates future errors by analyzing the rate of change, thereby improving the system's stability and dynamic response. The key parameters of the PID controller are the proportional gain (Kp), integral time constant (Ti), and derivative time constant (Td). Fig. 3 presents the block diagram of the PID controller applied to LFC.

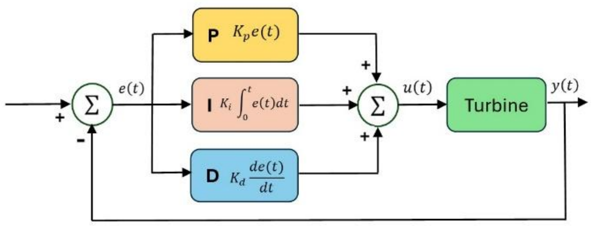

Figure 3: PID Controller Designed For LFC

The time-domain representation of the PID controller's output is expressed in Eq. 1:

$$u(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt} \quad (1)$$

In this equation, K_p, K_i and K_d denote the proportional, integral, and derivative gains of the controller, respectively, while $e(t)$ represents the error signal (ACE) for the load frequency control (LFC).

3. System Methodology

3.1 Jaya Optimization Algorithm

The Jaya optimization algorithm is employed to tune the PID parameters for the Load Frequency Control (LFC). In this study, a population size of 10 and 100 iterations were selected. The three design variables under consideration are Kp1, Ki1 and Kd1. Each candidate solution 'x' within the population represents a set of these design variables (Kp1, Ki1, Kd1). The best solution 'Best' in the population for a given iteration is identified by the minimum value of the objective function, while the worst solution 'Worst' corresponds to the maximum value. The modified solution 'xnew' is generated by updating the positions of candidate solutions relative to the Best and Worst solutions. This modification involves adjusting the design variables to improve the objective function's value. The candidate solution 'x' is then replaced by 'xnew' if the latter provides a better objective function value 'fnew'.

The search space is constrained by predefined minimum and maximum parameter values. Initial populations are generated within these bounds, and the objective function evaluates the error in the system's frequency response. The Jaya algorithm identifies the Best and Worst solutions in each generation and updates the candidate solutions iteratively. This process ensures convergence towards the optimal proportional (K_p), integral (K_i), and derivative (K_d) gains required for regulating the LFC system frequency.

The methodology for implementing the Jaya algorithm to determine the optimal PID parameters is depicted in Figure 4.

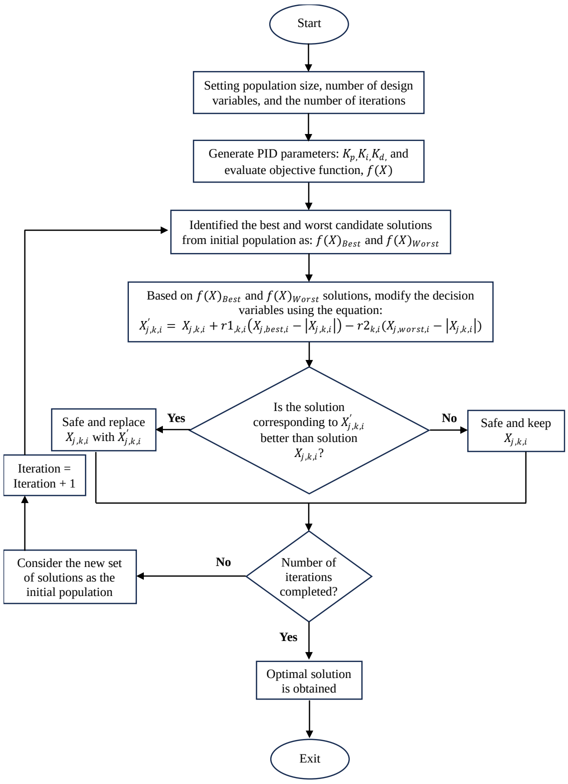

Figure 4: Flow Chart of JAYA Algorithm Applied To LFC

3.2 Artificial Neural Network

The integration of Artificial Neural Networks (ANNs) into Load Frequency Control (LFC) systems significantly enhances their performance by leveraging adaptive learning capabilities. This integration enables the ANN controller to learn the LFC model's behavior by training on its input and output data. The primary objective is to accurately predict the controller's output signal based on the Area Control Error (ACE).

Fig. 5 illustrates the typical architecture of an ANN model. A feedforward ANN structure consists of three primary layers: input, hidden, and output. Depending on the number of layers, ANN models can be categorized into three types: single-layer, multi-layer, and radial-layer networks. Among these, multi-layer feedforward networks are widely applied in machine learning due to their biologically inspired architecture, which facilitates data reception, processing, and transmission, mimicking neural functions in the brain. The layers are interconnected through neurons, with weights and biases determining the strength of these connections. The weighted summation of inputs is calculated using mathematical operations, as described in Eq. (2):

$$S_j = \sum_{i=1}^{n} w_{ij} x_j + bj \tag{2}$$

x_j represent the input signal value, w_{ij} denotes the weights between connected layers, bj is the weight value attributed to the nodes, and n is the total number of input signal. The backpropagation (BP) algorithm is typically employed to adjust these initial weights. The sigmoid activation function, often used to detect the output signal, is mathematically expressed in Eq. (3):

$$f(s) = \frac{1}{1 + e^{-sj}} \tag{3}$$

The core principle of this methodology lies in optimizing ANN performance by iteratively refining the weights of interconnections. This process generates output signals through predictive computations based on gradient descent, incorporating weight adjustments (Δw), as detailed in Eq. (4).

$$(t) = \eta w_{ji}^{l}(t-1) + \mu \, \Delta w_{ji}^{l}(t) \tag{4}$$

In this equation, $w_{ji}^{l}(t)$ represents the current training weight, $w_{ji}^{l}(t-1)$ is the previous training weight, whereas η is the learning rate, and μ is the momentum coefficient. The BP algorithm operates in two stages: forward propagation and backward propagation. During each iteration, the weights of the ANN are continually updated, and the mean squared error (MSE) between the predicted and actual values is calculated using Eq. (5):

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[Y_j(i) - T_j(i) \right]^2 \tag{5}$$

where variables *n* and *m* represent the number of input data points and output signals, respectively, while $Y_j(i)$ and $T_j(i)$ denote the actual and predicted outputs.

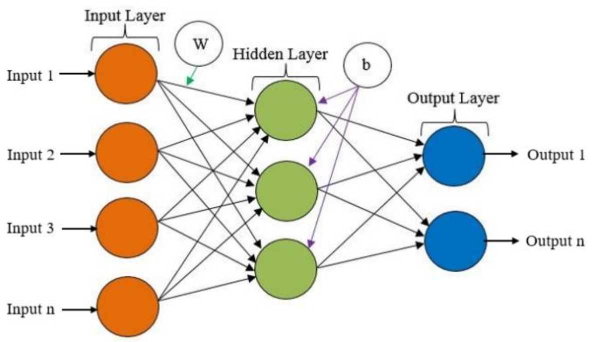

Figure 5: Structure of artificial neural network (ANN)

4. Results and Simulation

The performance of load frequency control for a single-area power system network was evaluated using MATLAB Simulink. The study compared four control strategies: conventional PID, ANN-PID, JAYA-optimized PID, and ANN-JAYA-PID. Simulations were conducted over a duration of 30 seconds, with step-load disturbances of 10% and 20% introduced at t = 5 seconds.

Tables 2 and 3 present the results for these step-load perturbations, including metrics such as maximum overshoot, maximum undershoot, transient time, and ITSE value. The findings demonstrate that the proposed ANN-based controller effectively trains and predicts outcomes that closely align with the optimized values. Specifically, Table 2 highlights the performance under a load variation of 0.1 p.u. For the PID controller tuned in MATLAB, the gain parameters are provided K_p= 1.9809, K_i = 7.8513 and K_d= 0.1200 whereas the JAYA-optimized PID controller achieves gains of K_p= 5.000, K_i = 2.4596 and K_d= 0.2506.

Table 2: Comparison Performance for SLP=0.1 P.U

No.	Controller Type	Transient time (s)	Overshoot (pu)	Undershoot (pu)	ITSE
1	PID Controller	6.4413	0.0168	-0.0500	0.2072
2	ANN tuned PID	6.1177	0.0129	-0.0480	0.5830
3	JAYA Optimized PID	5.4806	0.0066	-0.0500	0.1599
4	ANN-JAYA-PID	5.7914	0.0051	-0.0490	0.2506

Table 3: Comparison Performance for SLP=0.2 P.U

No.	Controller Type	Transient time (s)	Overshoot (pu)	Undershoot (pu)	ITSE
1	PID Controller	6.4430	0.0336	-0.1000	0.8282
2	ANN tuned PID	6.3789	0.0232	-0.0934	8.4830
3	JAYA optimized PID	5.4716	0.0135	-0.1000	0.6393
4	ANN-JAYA-PID	5.9931	0.0121	-0.0978	1.1770

The comparative profiles of frequency deviation in a single-area power system for all the controllers following an SLP of 10% and 20% are shown in Fig. 6-7. System based on ANN-based controller manages to deliver results close to those of an optimized controller.

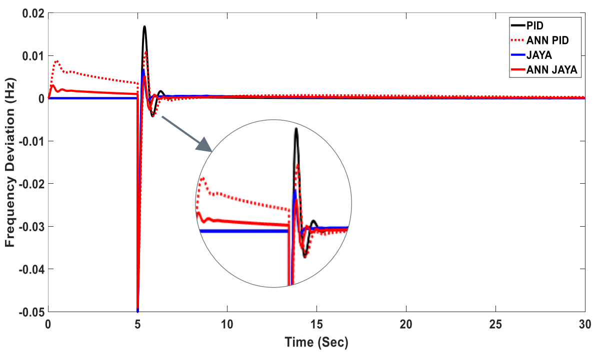

Figure 6: System response for all the controllers at 10% SLP

Controller based on ANN JAYA optimized PID gives better results compared to conventional ANN in terms of overshoot, transient time, and ITSE error. Fig.8-9 shows the comparison between the conventional ANN PID and ANN JAYA PID at SLP 0.1 and 0.2 respectively. Overall, the maximum overshoot of ANN JAYA is reduced than the conventional. This indicates that the ANN-JAYA-PID controller has better performance in minimizing the initial deviation from the setpoint. Further observed the transient time for ANN JAYA is shorter where it reaches the steady

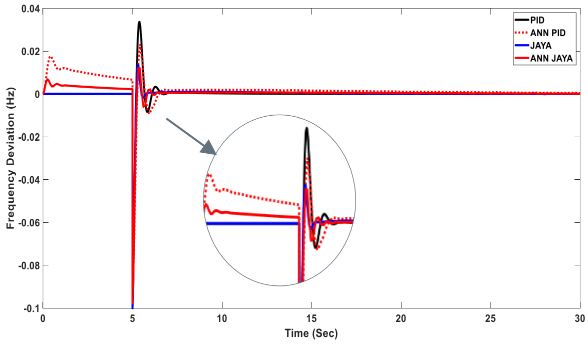

Figure 7: System response for all the controllers at 20% SLP

state more quickly, improving the system's overall response. The ITSE value for ANN JAYA was reduced by more than 50% providing better overall system performance by reducing the cumulative squared error over time.

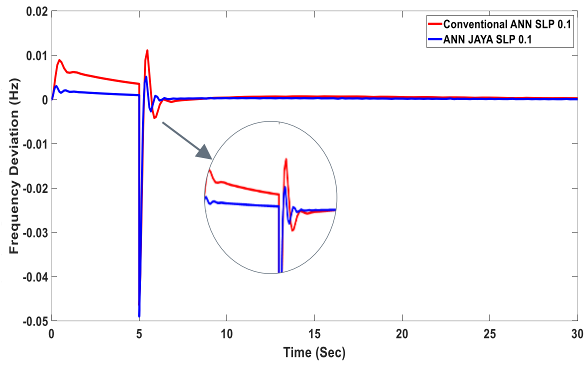

Figure 8: Comparison of Frequency Response for Conventional ANN and ANN JAYA for 10% SLP

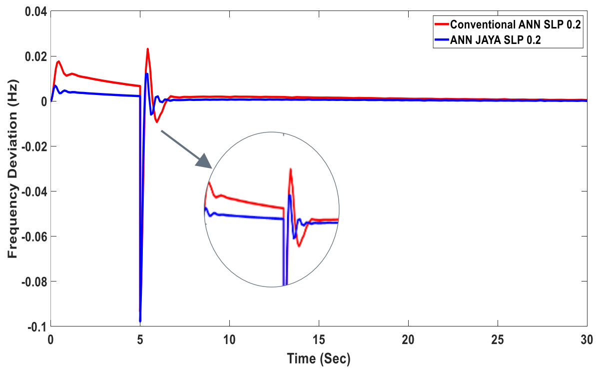

Figure 9: Comparison of Frequency Response for Conventional ANN and ANN JAYA for 20% SLP

To further investigate the robustness of the designed controller, the SLP for both ANN controllers varied between -20% to +20%. The system response in Table 4-7 shows that the controller was successfully generalized from the training data and can effectively handle load variation. The results indicate that the designed controller is resilient to such uncertainties.

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Table 4: Performance of ANN PID Controller when Fluctuation at SLP 0.1

Fluctuation in SLP	SLP	Transient Time (s)	Max.Ovs (p.u)	Max. Undershoot (p.u)	ITSE
Decrease 20%	0.08	6.1571	0.0089	-0.03647	2.2870
Decrease 10%	0.09	6.2540	0.0095	-0.04147	2.0490
ANN reference model	0.10	6.2487	0.0110	-0.04647	1.8380
Increase 10%	0.11	6.8944	0.0122	-0.05147	1.6520
Increase 20%	0.12	6.7011	0.0189	-0.05647	1.7120

Table 5: Performance of ANN PID Controller when Fluctuation at SLP 0.2

Fluctuation in SLP	SLP	Transient Time (s)	Max.Ovs (p.u)	Max. Undershoot (p.u)	ITSE
Decrease 20%	0.18	6.6225	0.0204	-0.08336	9.0580
Decrease 10%	0.19	7.053	0.0227	-0.08836	8.7390
ANN reference model	0.20	6.3789	0.0232	-0.09336	8.4830
Increase 10%	0.21	6.4182	0.0231	-0.09836	8.2410
Increase 20%	0.22	6.3236	0.0248	-0.1034	8.0150

As seen in Table 4 and Table 5, the ANN PID controller demonstrates increasing maximum overshoot and undershoot values with higher fluctuations in SLP, indicating heightened sensitivity to changes in load conditions. For instance, at a 20% increase in SLP from the reference model in Table 4 (SLP = 0.12), the maximum overshoot rises to 0.0189 pu, while the maximum undershoot deepens to -0.05647 pu, with a transient time of 6.7011 seconds and an ITSE of 1.7120. Similarly, in Table 5, at a 20% increase in SLP from the reference model (SLP = 0.22), the maximum overshoot further increases to 0.0248 pu, and the undershoot reaches -0.1034 pu, with a transient time of 6.3236 seconds and an ITSE of 8.0150. These trends highlight the ANN PID controller's dependence on precise load condition modelling and its potential vulnerability to substantial load fluctuations.

Table 6: Performance of ANN JAYA PID Controller when Fluctuation at SLP 0.1

Fluctuation in SLP	SLP	Transient Time (s)	Max.Ovs (p.u)	Max. Undershoot (p.u)	ITSE
Decrease 20%	0.08	5.5995	0.0030	-0.03902	0.2311
Decrease 10%	0.09	5.8144	0.0044	-0.04402	0.2390
ANN reference model	0.10	5.7914	0.0051	-0.04902	0.2506
Increase 10%	0.11	5.7953	0.0058	-0.04927	0.2524
Increase 20%	0.12	5.8028	0.0052	-0.04942	0.2520

Table 7: Performance of ANN JAYA PID Controller when Fluctuation at SLP 0.2

Fluctuation in SLP	SLP	Transient Time (s)	Max.Ovs (p.u)	Max. Undershoot (p.u)	ITSE
Decrease 20%	0.18	6.0411	0.0097	-0.08779	1.1370
Decrease 10%	0.19	5.9396	0.0105	-0.09279	1.1530
ANN reference model	0.20	5.9931	0.0121	-0.09779	1.1770
Increase 10%	0.21	5.7911	0.0122	-0.09804	1.1780
Increase 20%	0.22	5.9925	0.0123	-0.09819	1.1790

Performance of the ANN JAYA PID controller demonstrates significantly improved robustness and adaptability to fluctuations in SLP when compared to the ANN PID controller. This is evidenced by notably lower maximum overshoot and undershoot values across various SLP conditions. For instance, at a 20% decrease in SLP from the reference model with an initial SLP of 0.1, the ANN JAYA PID controller achieves a maximum overshoot of only 0.0030 pu and a maximum undershoot of -0.03902 pu. Similarly, with an initial SLP of 0.2 under a 20% decrease, the maximum overshoot is 0.0097 pu, and the maximum undershoot is -0.08779 pu. These values reflect a significant reduction in transient oscillations, thereby ensuring better stability and lower integral time square error (ITSE). Additionally, the transient times remain consistently low across scenarios, further emphasizing the controller's efficiency in stabilizing the system.

5. Conclusion

The study successfully demonstrates the integration of an ANN-based controller with a Jaya Algorithm optimized PID controller for a single area thermal system of the LFC model. The performance of different controllers was observed to validate the robustness of the ANN controller. The proposed PID controller, tuned using the Jaya optimization algorithm, shows superior performance compared to conventional methods. The robustness of the ANN-designed controller is validated across various load conditions, where its performance remains consistently close to the trained ANN model. Simulation results reveal that the ANN-JAYA PID controller significantly outperforms the ANN-PID controller by exhibiting lower overshoot, reduced transient response time, and improved overall system performance, as indicated by the Integral Time Square Error (ITSE). The ANN-JAYA PID controller achieves a reduction in overshoot by 60%, a decrease in transient time by 0.33 seconds, and an enhancement in ITSE by 57% for SLP 0.1. Where else for SLP 0.2, ANN-JAYA PID controller reduces overshoot by 47%, shortens the transient time by 0.39 seconds, and an enhancement in ITSE by 86%. These results highlight the potential of integrating ANN-based control strategies with advanced optimization techniques like Jaya Algorithm to achieve nearly optimal performance across a wide range of operating conditions.

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