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Optimization of FOPID Hydro Power Plant Load Frequency Control Using Zebra Optimization Algorithm

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ABSTRACT
The dynamic nature of the electric power system results in constant change in balance position of the system due to the difference between electric power demand and supply. This constitutes a power system frequency stability problem. Thus, a control process called load frequency control (LFC) is required in order to damp the fluctuations that results and various controllers ranging from ANN, PID and Fuzzy Logic have been applied. In this study, an intelligent FOPID controller is designed for ensuring the Load Frequency control of a hydro power plant. Zebra Optimization Algorithm used for determining the optimal FOPID parameters and the optimization process was evaluated using the Integral Time absolute Error (ITAE) Error and Integral Time Square Error (ITSE) Criteria. Performance analysis of the ZOA was evaluated using Particle Swarm Optimizer (PSO). Result obtained from the study showed that the FOPID controller designed by ZOA-ITAE achieved the shortest settling time compared to the other methods. Specifically, the percentage comparison reveals that ZOA_ITAE outperforms all other controllers in terms of settling time, making it the most efficient choice. Compared to ZOA_ITAE, PSO_ITAE exhibits a 36.05% longer settling time. Similarly, ZOA_ITSE takes 25.89% longer, showing that while ZOA-based tuning is effective, ITSE performs slightly worse than ITAE. The worst performer is PSO_ITSE, with a 56.32% increase in settling time. This suggests that ZOA-based optimization, particularly with ITAE, is the best approach for achieving faster system stability.

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I. INTRODUCTION

With the advancement in technology, there is an immense increase in the demand of electrical energy that has not only become challenge for its production but also its stability. Majeed Butt et al. (2021) stated that this rising demand is growing the complexities of power grids by increasing requirement for greater reliability, efficiency, security and environmental and stability concerns. Furthermore, the introduction of certain disturbing loads, major changes in network topology, the increasing strains on transmission lines, etc. are dangerously pushing the power system towards and beyond stability limits, thus creating instabilities and power quality disturbances (PQD) problems Alimi et al. (2020).

With respect to power system stability, it is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact as stated byHatziargyriou et al. (2021). A TASK force set up jointly by the IEEE Power System Dynamic Performance Committee and the CIGRE Study Committee (SC) 38, currently SC C4 – System Technical Performance, had addressed the issue of stability definition and classification in power systems from a fundamental viewpoint and had closely examined the practical ramifications. This joint effort involving IEEE PES and CIGRÉ was comprehensive and clearly contrasted the electromechanical phenomena associated with various classes of power system stability behavior in comparison to earlier efforts Hatziargyriou et al., (2021) and Shair et al. (2021).

In power systems, frequency stability is an important index of power quality. Any sudden load perturbation can cause the deviation of tie-line exchanges and the frequency fluctuations. Therefore, to ensure the power quality, a load frequency control (LFC) system is needed. The goal of LFC is to return the frequency to its nominal value and minimize the unscheduled tie-line power flows between interconnected control areas. With the increase in size and complexity of modern power systems, the system oscillation might propagate into wide area resulting in a wide-area blackout Tan et al. (2017). Furthermore, controlling the system in emergency situations and sudden load changes such as short-term interruption is necessary to prevent frequency deviations (DokhtShakibjoo et al., n.d.). In practice, there are non-linearities in LFC system. Typical non-linearities in

LFC include governor dead band (GDB) and generation rate constraint (GRC). GRC is a physical constraint on the rate of the change in the generating unit due to physical limitations of turbine Tan et al., (2017).

Although intelligent control strategies can successfully handle the frequency stability problems, they exhibit several limitations linked to the increased computational complexity, and the requirement for deep learning procedure and powerful inference tool. Hence, several industrial applications are still utilizing many classical linear and nonlinear control methods, which have been employed for LFC function in electrical power systems due to their simplicity in structure and their economical cost compared to other control techniques. The main control structures are the integral, proportional integral (PI) controller, proportional integral derivative (PID) controller, Neuron-fuzzy.Mohamed et al. (2020)

Given the dynamic behavior of electrical power systems, these require modern optimization techniques to achieve a solution that satisfies the problem conditions, fuzzy based, neural network-based methods, and metaheuristics. Generally, optimization problems involve finding the best feasible solution from a set of possible solutions for a problem at hand. It also aims to maximize or minimize a fitness function by searching and selecting its best values. In LFC problems, the optimization problems related to electric power systems under study are continuous and seek to minimize the proposed objective function.Emad A. Mohamed & Emad M. Ahmed (2024).

II. MATERIAL AND METHODS

The required materials and methods proposed for this research work are discussed in this section. A systemic modeling approach in MATLAB/Simulink environment is adopted for realizing the set aim and objectives of the study. The evaluated power system consists a hydro-electric power plant system, Artificial Neural Network (ANN) controller, controller and PID controller and FOPID controller for Load Frequency Control (LFC).

2.1 METHODS OF THE STUDY

A step-by-step modeling approach of the various parts of a hydro-electric power plant system for Load Frequency Control (LFC) is adopted in carrying out this study. A general model of the method adopted for this study is as shown in Figure 1.Thus, respective fundamental mathematical relationships considered for the modeling are presented in this sub-section.

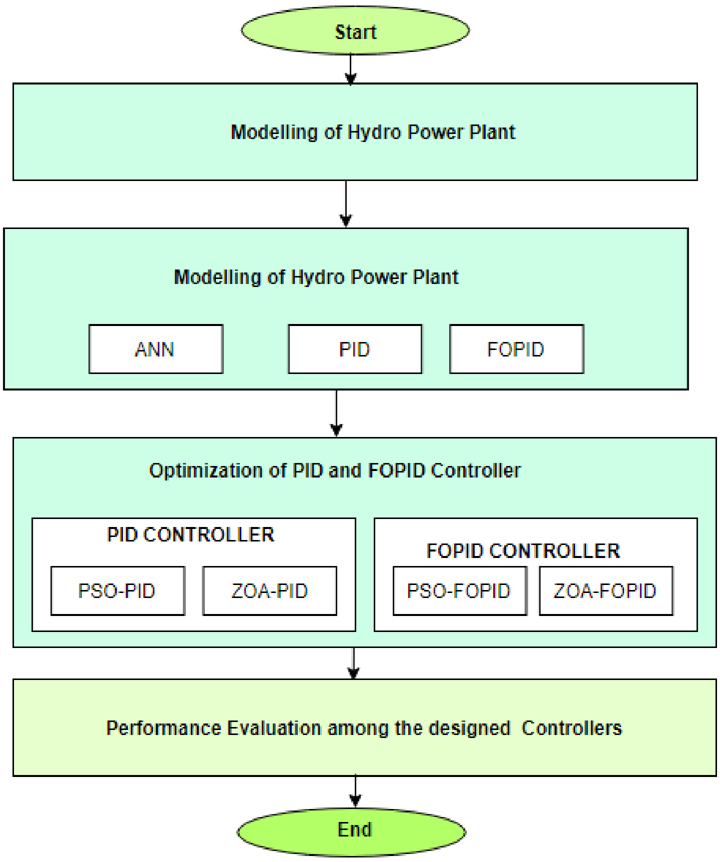

Figure 1: The Flow of The Methodology

Phase I: Hydro power plant model

To model the Hydro Power Plant, the modeling equations used are as presented from Equation 1 through Equation 6 as stated by K. Kumari & G. Shankar (2016)and Sabo et al. (2022).

$$\Delta\omega_{(s)} = \frac{1}{2Hs}(\Delta Pm(S)\text{-}\Delta Pe(s)) \quad (1)$$

The prime mover is the source of mechanical power from the hydraulic turbine**.**

$$G_{T(s)}=\frac{\Delta P_m(s)}{\Delta P_v(s)}=\frac{1}{1+s\tau_t} \quad (2)$$

Where;

ΔPm is Change in mechanical output power,

ΔPv isChange in the steam valve position,

τtis Turbine time constant.,

The speed governor serves as a comparator

$$\Delta P_g(s) = \Delta P_{ref}(s) \text{-}\frac{1}{R}\,\Delta\omega(s) \quad (3)$$

Where;

$P_g$is Power output of the governor.

$P_{ref}$is Reference set power.

Relationship between governor input and valve opening

$$\Delta P_v(s) = \frac{1}{1+s\tau_t}\Delta P_g(s) \quad (4)$$

The load model is as expressed in Equation 5

$$\Delta P_e(s) = \Delta P_L{+}D\Delta w \quad (5)$$

Where;

P_e = electrical power,

D= damping ration

The interaction between the load model and the frequency can be expressed as;

$$\Delta P_L(freq) = D\Delta\omega = \frac{\Delta P_L(freq)}{\Delta\omega} \quad (6)$$

PhaseII: ANN Controller Modelling

The ANN network is a multilayer simple network which consist three layer and they are, an input layer, a hidden layer and an output layer. The main objective of this model is that it can predict the actual output signal of the operation system based on random training data by converting the random collected data into a nonlinear mapping between input nodes and output nodes as shown in Figure 2.

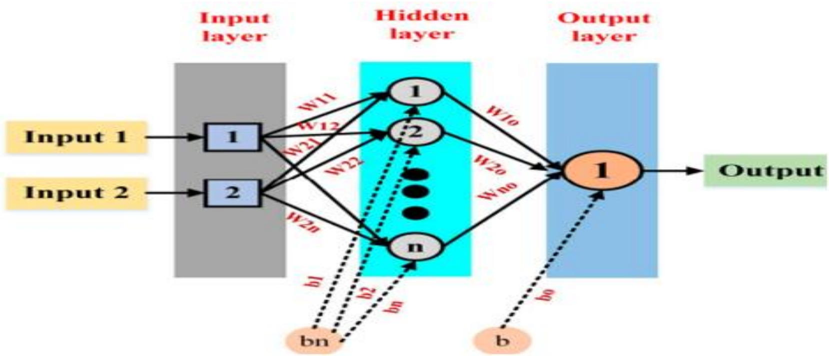

Figure 2: Artificial Neural Network Model

The Equations from 7 to 9 represent the ANN Algorithm as referenced by K.Kumari& G. Shankar, (2016).

$$S_j = \sum_{i=1}^{n} w_{ij}x_j + b_j \quad (7)$$

$x_{j,w_{ij}}$ input signal, connection weight where n is the input signal

$$f_{(s)} = \frac{1}{1+e^{-sj}} \tag{8}$$

Step change value of the weight

$$w_{ij}^{l}(t) = \eta\omega_{ij}^{l}(t-1) + \mu\Delta\omega_{ij}^{l}(t) \tag{9}$$

$w_{ij}^{l}(t)$ represent current training weight, $\eta\omega_{ij}^{l}(t-1)$ previous training weight

PhaseIII:PID Controller Modelling

For the power system model considered in this study, the PID controller parameters are represented by the following equations (Ali & Abd-Elazim, 2013)

$$G_{PID(s)} = K_P(s) + \frac{K_i}{s} + K_{d(s)} \tag{10}$$

A simplified block diagram of a plant controlled by a PID controller is shown in Figure 3.

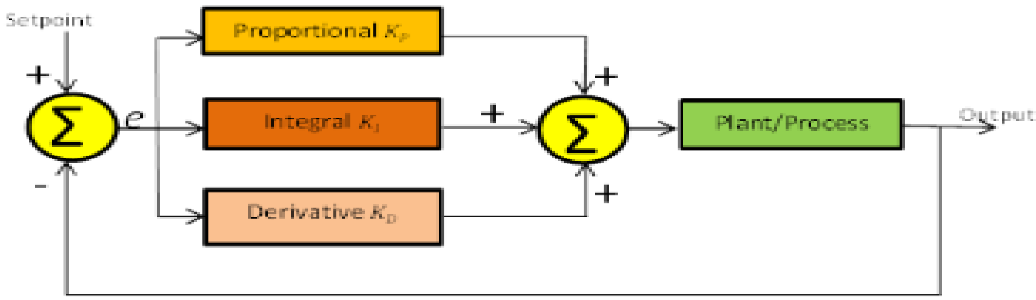

Figure 3:PID Controller Structure

Phase IV: FOPID Modelling

Recently, the emergence of fractional calculus has made possible the transition from classical models and controllers to those described by differential equations of non-integer order. Thus, fractional-order dynamic models and controllers were introduced.The controllers have an integrator order λ and differentiator order μ and these two extra parameters provides an added degree of freedom in the performance of controller that makes FOPID controller performance better than conventional PID controller. Its mathematical relationship is represented in equation 11 as presented by Rajesh, (2019) and Tepljakov et al. (2018).

$$G_c\ (s) = \frac{U(s)}{E(s)} = K_P + K_I s^{-\lambda} + K_D s^{-\mu} \tag{11}$$

Where;

KP = gain value of P controller,
KI = gain value of I controller,
KD = gain value of D controller,
λ = real non integer positive number (order of integration)
μ = real non integer positive number (order of differentiation).

The MATLAB Simulink Model for the FOPID controller is as represented in Figure 4

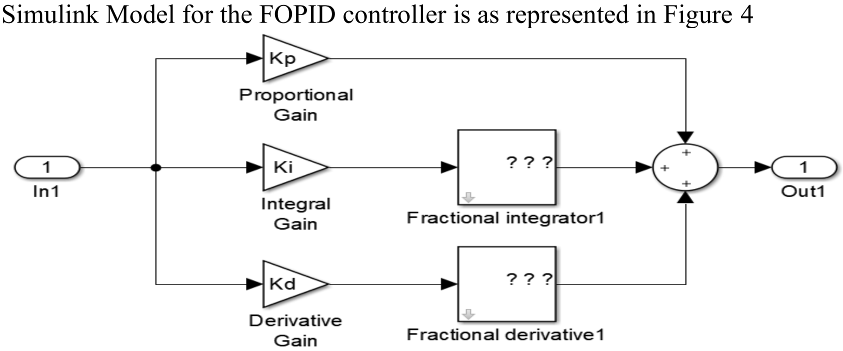

Figure 4: FOPID Controller MATLAB Simulink Model

III. CASE STUDY: FREQUENCY SABILITY ENHANCEMENT OF ISOLATED POWER HYDROPOWER SYSTEM

Frequency stability is vital in isolated hydropower systems, where load variations can cause significant deviations. Load Frequency Control (LFC) regulates generation output to maintain system frequency within permissible limits. Conventional PID controllers are widely used but often struggle with nonlinearities and fast load changes. Advanced controllers, such as Fractional Order PID (FOPID) and Artificial Neural Networks (ANN), offer improved performance through flexible tuning and adaptive learning. Two Optimization techniques; Particle Swarm Optimization (PSO) and Zebra Optimization Algorithm (ZOA)are used to further enhance controller effectiveness, reducing overshoot and settling time. Combining LFC with ANN and optimized PID/FOPID controllers provides a robust solution for maintaining reliable and stable operation in isolated hydropower systems.

3.1 ANNTraining

The input and target output data for training the ANN were obtained from simulations of the Load Frequency Control (LFC) model.

I. Input variables (frequency deviation)

II. Output control signals were pre-processed and transposed to match the expected dimensions for the neural network.

A feedforward neural network (FNN) was constructed using the new function with the following specifications:

I. Input range: Defined by minmax(I).

II. Network structure: Four layers:

III. Layer 1: 3 neurons with log-sigmoid (logsig) activation

IV. Layer 2: 20 neurons with tangent-sigmoid (tansig) activation

V. Layer 3: 20 neurons with tangent-sigmoid (tansig) activation

VI. Output Layer: 1 neuron with linear (purelin) activation

VII. Training algorithm: Levenberg–Marquardt backpropagation (trainlm) for fast convergence.

Artificial Neural Network Training was carried out and the trained Network obtained was used in simulating the power system.
The Training of the Load Frequency Control based ANN was carried out and the MATLAB network obtained are as shown in Figure 5.

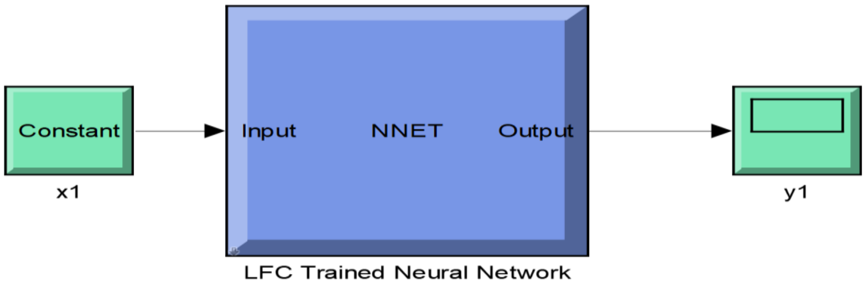

Figure 5: Trained Load Frequency Artificial Neural Network

The trained ANN model was then integrated into the LFC control loop to replace the traditional controller. Thus, the summary of the ANN setup parameters used for the ANN LFC design is as represented in **Table 1**

Table 1: Summary of the ANN Design for LFC

S/N	Design Component	Parameter
1.	Network Type	Feedforward neural network (4 layers)
2	Activation Functions	logsig → tansig → tansig → purelin
3.	Training Algorithm	Levenberg–Marquardt (trainlm)
4	Inputs/Outputs	From the Load Frequency Control Model
5.	Training Goal (Stopping criteria)	MSE < 1e-12 or max 10,000 epochs
6.	Initialization	Random weights and biases with initial.

3.2 Optimization Of PID and FOPID Controller for LFC

In carrying out the optimization for the PID and FOPID controller, Zebra Optimization Algorithm (ZOA) and Particle Swarm Optimizer (PSO) are proposed. The objective function of the optimization, error criteria and the constraint are presented in this subsection

ZOA is bio-inspired metaheuristic algorithm. Its fundamental inspiration is the behavior of zebras in nature. Inspired by zebra foraging and defense behavior, Zebra Optimization Algorithms have been proposed byHe et al., (2024).ZOA simulates the foraging behavior of zebras and their defense strategy against predators' attacks. The ZOA steps are described in Figure 6.

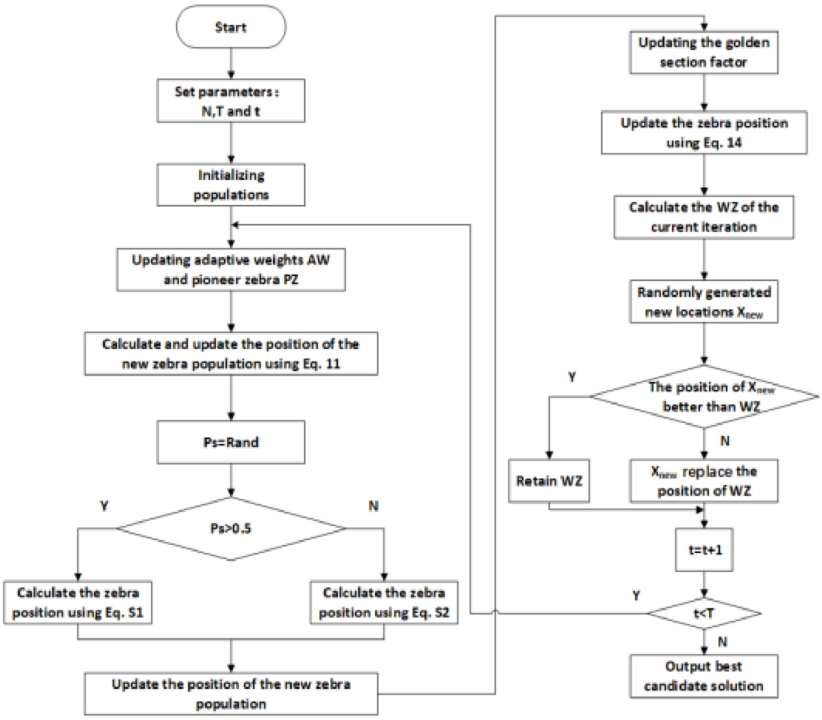

Figure 6: Zebra Optimization Algorithm Flow Chart

The particle swarm optimization (PSO) technique is a well-known population-based metaheuristics technique to solve optimization problems. They continuously update their position, according to their own best position and the best position of the entire swarm, and regroup themselves, resulting in an optimal formation individual(Jain et al., 2022)

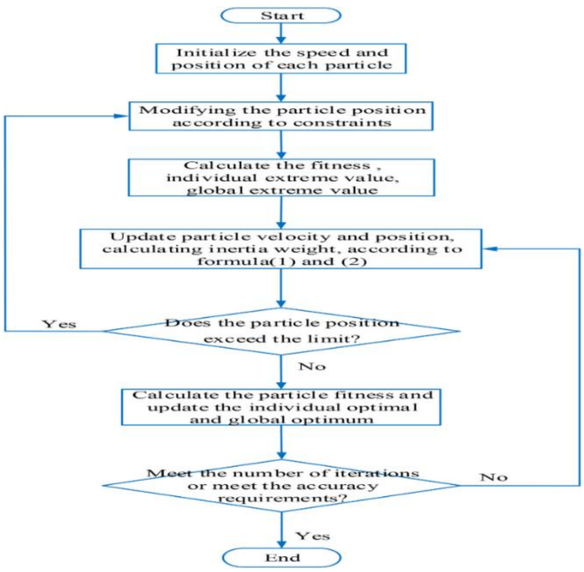

Figure 7:Particle Swarm Optimization Flow chart Shyr et al. (2010).

As shown in Figure 7, this algorithm simulates the social behavior of birds within the flock to attain the target of food. With thecombination of both self and social experience, a swarm of birds approaches their target of food.

3.2.1 Optimization Of PID and FOPID Controller for LFC

In this work, FOPID controller was optimized usingZebra Optimization Algorithm(ZOA) and compared to Particle Swarm Optimizer (PSO) based PID and FOPID controller for evaluation.
Minimizing the signal obtained at the output of the FOPID controller($\Delta\alpha$) defines is the objective function (J) and it will be evaluated around the ITAE performance index as shown in Equation 12

$$\text{J-(ITAE)} = \int_0^\infty t|\Delta\alpha| \, dt. \quad (12)$$

Where J is the objective function of the controller, evaluated using ITAE error criterion.

3.2.2 Optimization Constraint

In designing the PID controller, three optimization parameters (Kp, Ki, Kd) were tuned and defined with lower (K_p^{min}, $K_i^{min}$and K_d^{min}) and upper boundaries(K_p^{min}, $K_i^{min}$and K_d^{min}).

For the FOPID controller design, five parameters (Kp, Ki, Kd, λ, μ), were tuned for optimal performance of the power system. The lower bounds are (K_p^{min}, $K_i^{min}$and K_d^{min}, λ^{min} and μ^{min}) and the upper bounds are (K_p^{max}, K_i^{max},K_d^{max}, λ^{max} and μ^{max}) represent the upper bound accordingly.

Thus, the objective function (J) will be minimized subject.

$K_p^{min} \leq K_p \leq K_p^{max}$
$K_i^{min} \leq K_i \leq K_i^{max}$
$K_d^{min} \leq K_d \leq K_d^{max}$
$\lambda^{min} \leq \lambda \leq \lambda^{max}$
$\mu^{min} \leq \lambda \leq \mu^{max}$

Table 2 shows the Optimization Parameter Setting adopted for the study.

Table 2: Optimization Parameter Setting

Parameter	PID Setting	FOPID Setting
Population size	100	100
Number of variables	3	5
Variables	K_P, K_I, K_D	K_P, K_I, K_D, λ and μ
Iterations	100	100
Lower boundary	[0, 0,0]	[0, 0,0,0,0]
Upper boundary	[20, 20,20]	[20, 20,20,2,2]

IV. RESULTS

At the end of the optimization and all necessary simulations, various results were obtained from which the performance of Load Frequency Controller was analyzed. The designed Artificial Neural Network (ANN), PID and FOPID controller for an isolated hydropower system was carried out in the study. The FOPID evaluated with the ITAE criteria produced the best result.

4.1 ANN REGRESSION AND SIMULATIONRESULT

For a successful ANN training the regressing value should approximately 1. The regression result for the trained ANN is as shown in Figure8

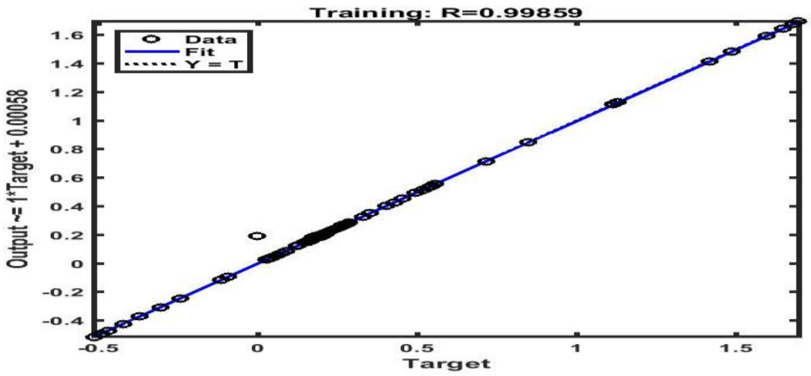

Figure 8: ANN Training Regression Result

Figure 9 shows the simulation result obtained by incorporating the trained ANN controller into the power system.

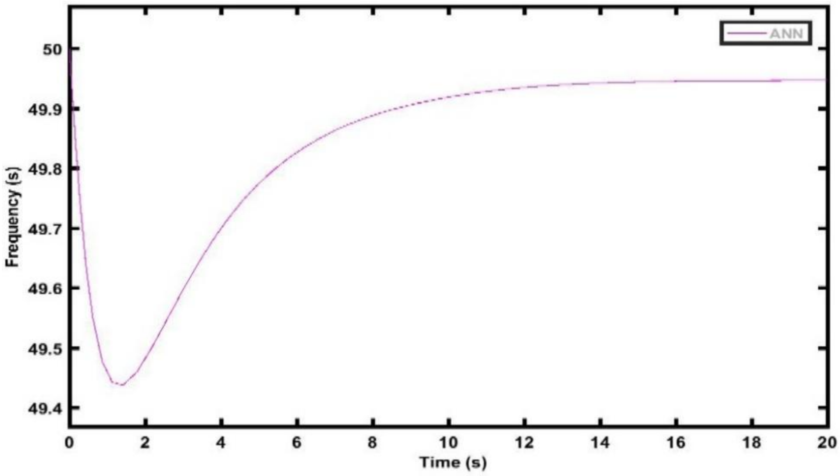

Figure 9: ANN Frequency Response

From the result in Figure 9, the settling of the ANN is 18.23 seconds.

4.2 PID CONTROLLER RESULT

The PID controller was designed and used in simulating the isolated power system. To obtain the Optimal PID parameters, Zebra Optimization Algorithm (ZOA) and Particle Swarm Optimizer (PSO) were used for the design.

For the PID design, the tunned parameters obtained are as represented Table 3

Table 3: PID Parameter OptimizationResult

OPTIMIZER	PID Parameter		
	Kp	Ki	Kd
PSO-ITAE	12.6872	19.8701	4.6321
ZOA-ITAE	13.5487	12.2348	4.5432
PSO-ITSE	13.2088	19.6532	5.96015
ZOA-ITSE	15.090	17.760	5.3240

The PID controller is designed with PID parameters shown in Table 3. Integral Time square Error was applied in evaluating the error and minimization of the error was carried out.

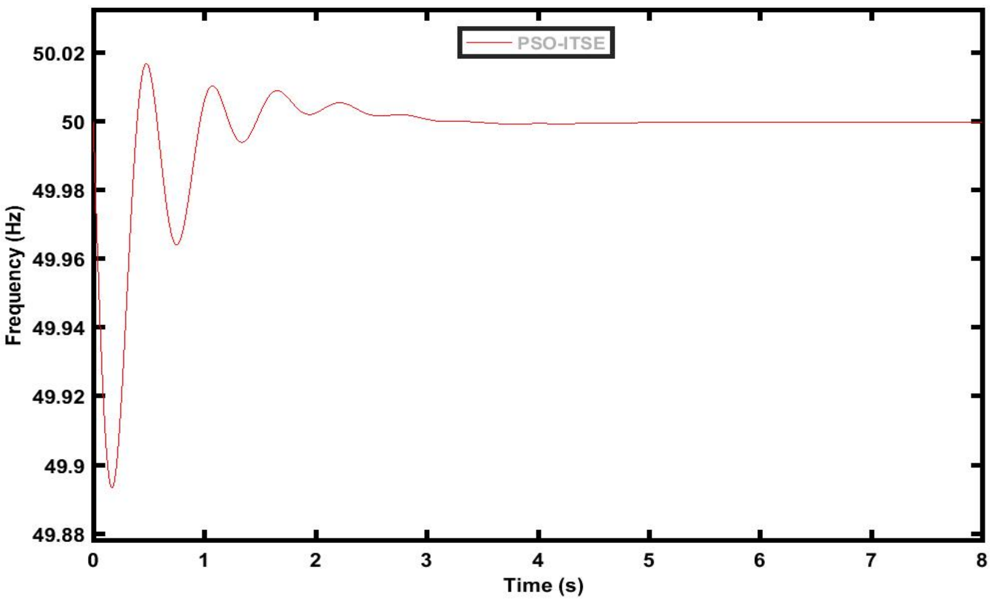

Figure 10: PSO-ITSE Frequency Response

The curve in Figure 10represents the frequency response under the control scheme optimized using PSO-ITSE. The response shows the system's frequency stabilizes after an initial fluctuation caused by a load disturbance. The settling time for the PSO-ITSE controller design is 4.92s

Similarly, ZOA-ITSE based controller design produced the frequency response in Figure11. For this result optimal tunning parameters obtained in the ZOA-ITSE optimization were used in designing the PID controller.

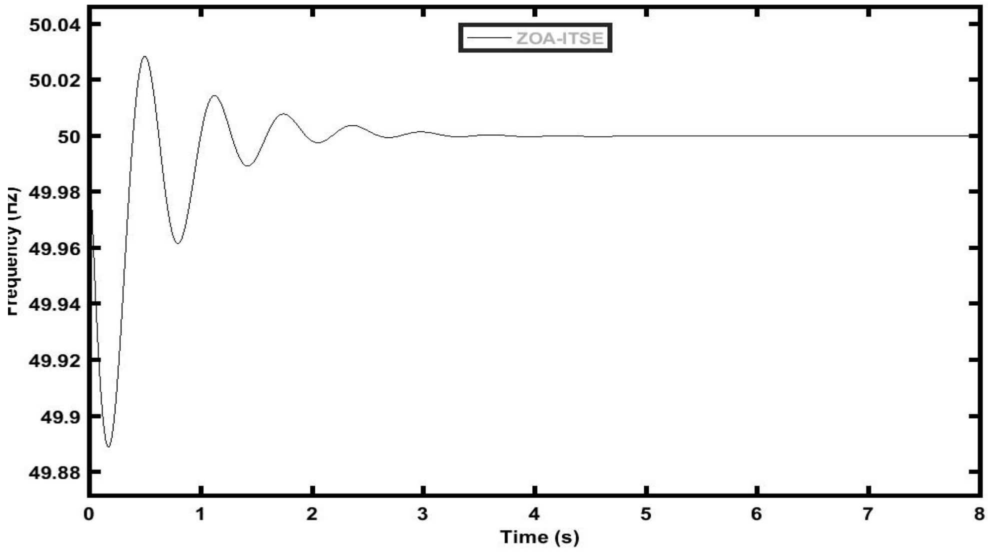

Figure 11: ZOA-ITSE Frequency Response

The curve in 11 shows the system's frequency stabilizes after an initial fluctuation caused by a load disturbance. The selling time for the PSO-ITSE controller design is 4.89

Figure12 shows the frequency curve for the PSO-ITAE based controller design.

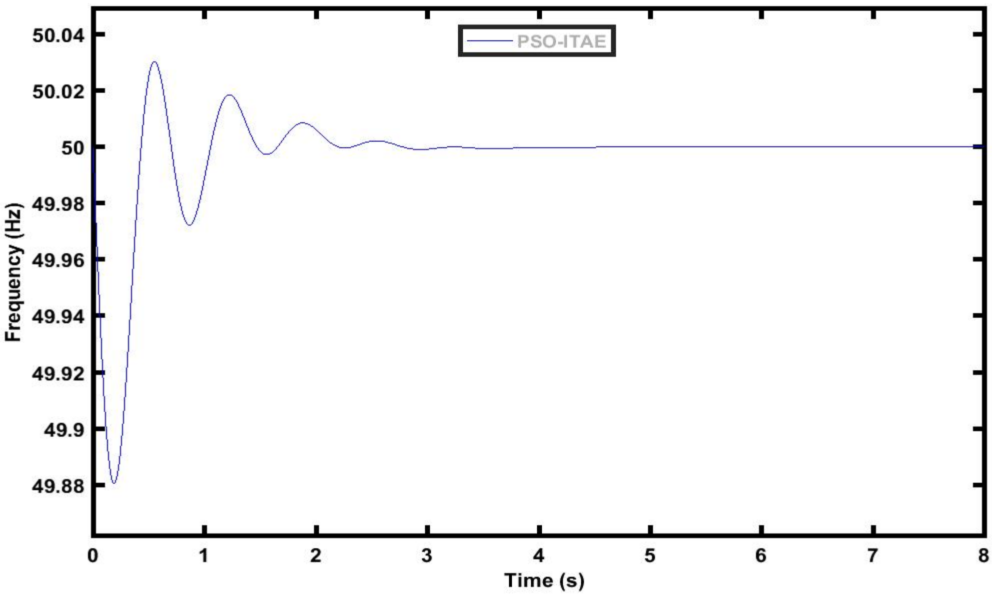

Figure 12: PSO-ITAE Frequency Response

As indicated curve in Figure 12, load disturbance results in frequency variation which was stabilized to the nominal frequency of 50Hz by the designed PID controller. A settling time of
the PSO-ITAE controller design is 4.507s

Accordingly, for the ZOA-ITAE based designed PID controller. The Frequency response it produced is as shown in Figure13.

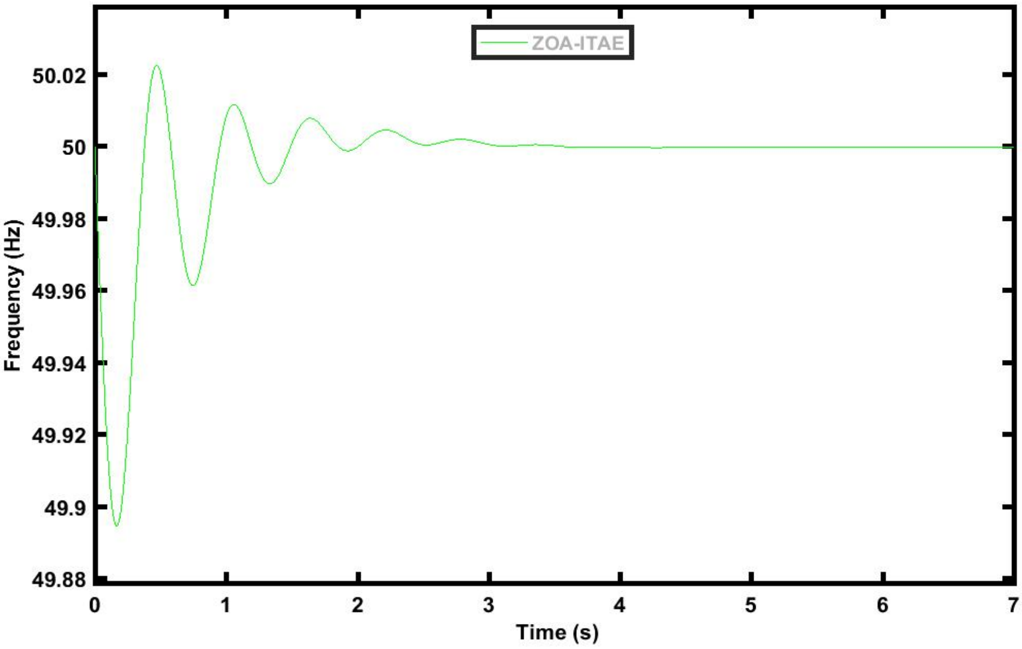

Figure 13: ZOA-ITAE Frequency Response

As shown in Figure 13, the load disturbance caused a deviation in frequency, which was successfully restored to the nominal frequency of 50 Hz using the designed PID controller. The ZOA-ITAE controller achieved a settling time of 4.075 seconds

Thus, the **ZOA-ITAE** results represent the best among the PID controllers analyzed in the study.

4.3 FOPID CONTROLLER RESULT

FOPID controller was designed and used in simulating the isolated power system. Zebra Optimization Algorithm (ZOA) and Particle Swarm Optimizer (PSO) were also used in the design to obtain the Optimal FOPID parameters.The obtainedFOPID parameters are as shown in Table 4.

Table 4: FOPID Parameter Optimization

	FOPID Parameter				
OPTIMIZER	Kp	Ki	Kd	λ	μ
PSO-ITAE	19.701	13.115	8.13	1.0121	1.1032
ZOA-ITAE	15.0001	13.011	4.39214	1.0123	1.1115
PSO-ITSE	17.9201	11.0516	7.0172	1.0246	1.1107
ZOA-ITSE	19.5	15.7	6.5429	1.0136	1.1045

The FOPID-ITSE controller aims to minimize the Integral of Time Square Error (ITSE). This objective focuses on reducing the magnitude of the error while penalizing long-lasting deviations from the nominal frequency (50 Hz). The FOPID controller is designed with tuning parameters represented in Table 4.

As illustrated in Figure 14, the load disturbance led to a frequency deviation, which was effectively restored to the nominal frequency of 50 Hz using the designed FOPID controller. The PSO-ITSE controller attained a settling time of 4.281 seconds.

For the ZOA-ITSE based FOPID controller design, the Frequency response obtained from the study is as indicated in Figure 15

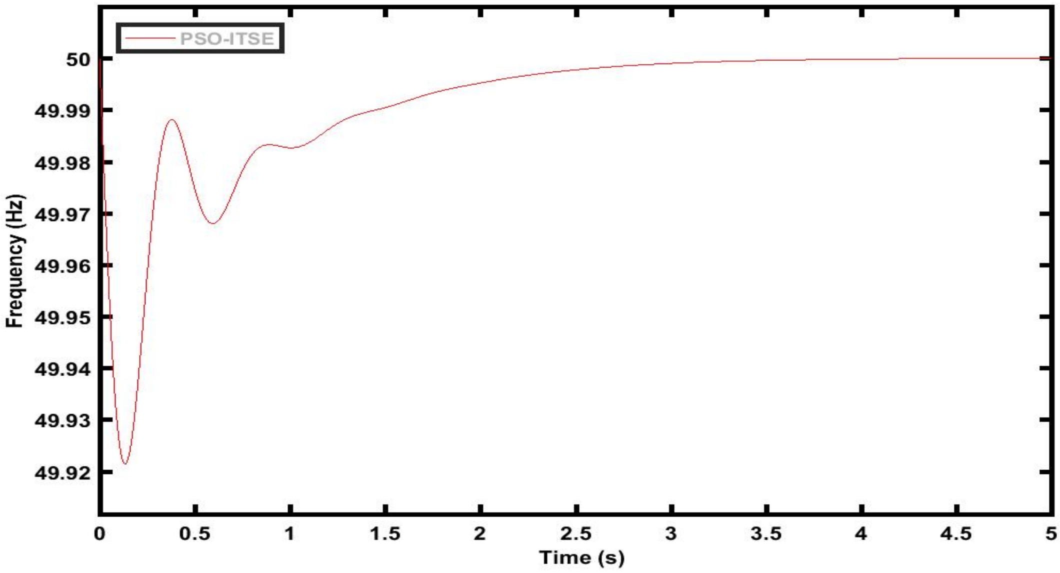

Figure 14: PSO-ITSE Frequency Response

As represented in Figure 15, frequency deviation was effectively restored to the nominal frequency of 50 Hz using the designed FOPID controller. The ZOA-ITSE-based FOPID controller attained a settling time of 3.726 seconds.

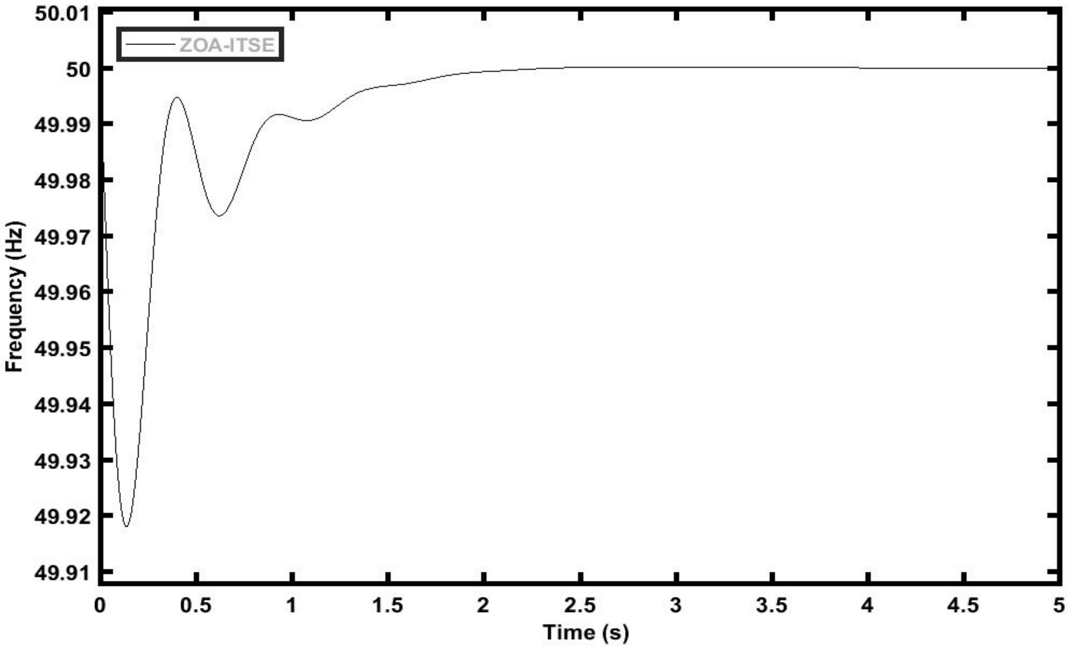

Figure 15: ZOA-ITSE Frequency Response

For a detailed analysis, the FOPID-ITAE (Fractional Order PID with Integral Time Absolute Error) controller was also designed to enhance the stability and performance of the power system by minimizing the Integral Time Absolute Error (ITAE). The result obtained from the PSO-ITAE and ZOA-ITAE for the FOPID controller are as represented in Figure 16 and Figure 17

The frequency response for the PSO-ITAE FPID controller is presented in Figure 16

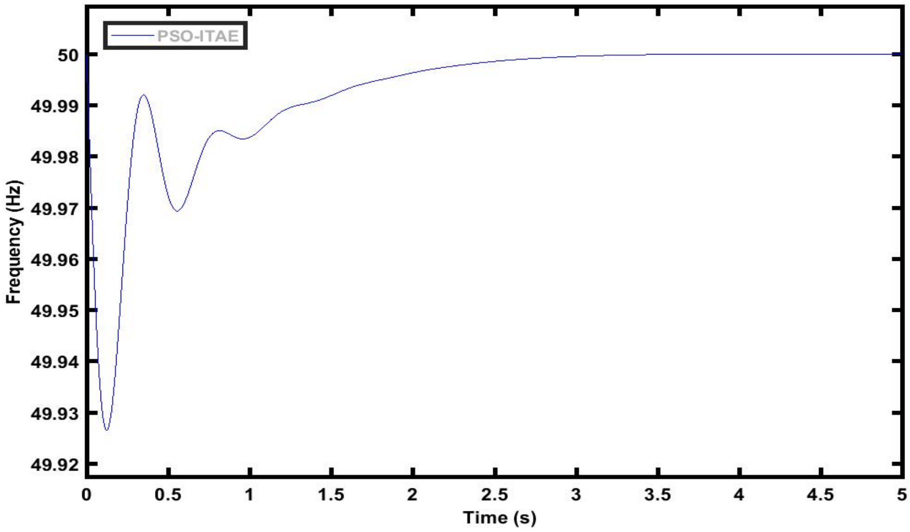

Figure16: PSO-ITAE Frequency Response

As illustrated in Figure 16, frequency deviation was restored to the nominal frequency of 50 Hz using the designed PSO-ITAE based FOPID controller. The controller attained a settling time of 3.448seconds.

The frequency response for the PSO-ITAE controller is presented in Figure 17.

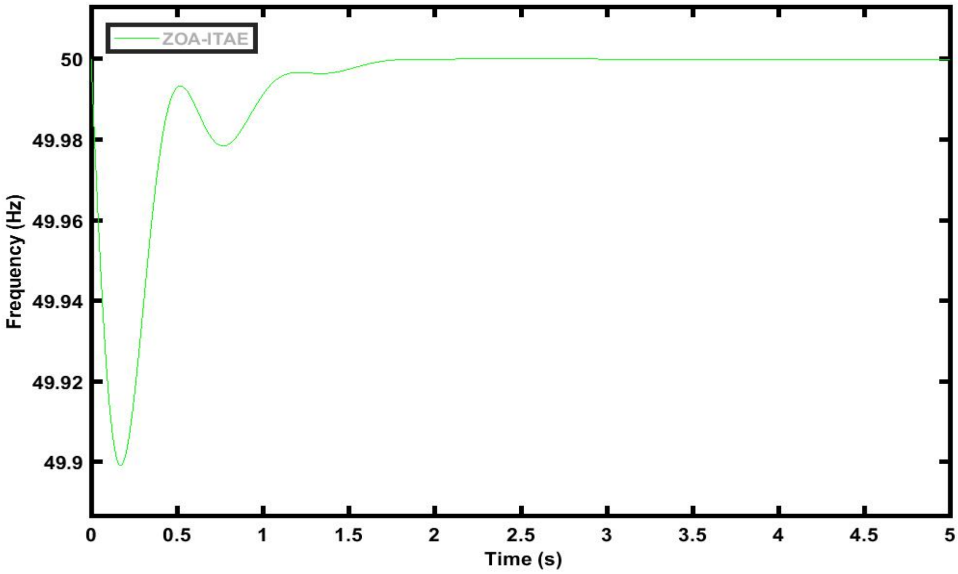

Figure. 17: ZOA-ITAE Frequency Response (FOPID)

Figure 17 shows the ZOA-ITAE Frequency Response in which deviation was successfully restored to the nominal frequency of 50 Hz using the designed FOPID controller. The ZOA-ITAE FOIPID controller achieved a settling time 2.739 seconds.

4.4 PERFORMANCE METRICS ANALYSIS

In Load Frequency Control (LFC) studies, performance metrics are crucial in evaluating the effectiveness of controllers. In this study the Four PID controllers were designed; PSO-ITSE, ZOA-ITSE, PSO-ITSE and ZOA-ITAE).

Thus, Table 5 shows the performance matrix of the controllers considered in the study.

Table 5: Performance Metrics analysis for PID

Controller	Performance Metrics analysis for PID		
	Settling Time (s)	**Rise Time**	**Overshoot (%)**
PID (PSO_ITAE)	4.507	159.274ms	25.949
PID (PSO _ITSE)	6.634	148.815ms	15.698
PID (ZOA_ITAE)	4.075	162.206ms	21.341
PID (ZOA _ITSE)	5.339	144.517ms	25.949

With respect to the Settling Time Analysis, ZOA-ITAE outperforms others with a 9.58% reduction in settling time compared to PSO-ITAE and a 38.56% improvement over PSO-ITSE.

For the Rise time Analysis, PSO-ITSE (148.815ms) has the fastest rise time. ZOA-ITSE (144.517ms) shows the best rise time but suffers from high overshoot while ZOA-ITAE (162.206ms) is slightly slower but more stable. From the Overshoot Analysis, PSO-ITSE (15.698%) achieved the lowest overshoot, indicating better damping performance, ZOA-ITAE (21.341%) is moderate while PSO-ITAE (25.949%) and ZOA-ITSE (25.949%) have the highest overshoot, leading to poor transient performance.

Similarly, four FOPID controllers were designed; PSO-ITSE, ZOA-ITSE, PSO-ITSE and ZOA-ITAE).

Table 6: Performance Metrics analysis (FOPID)

Controller	Performance Metrics analysis (FOPID)		
	Settling Time (s)	**Rise Time**	**Overshoot (%)**
FOPID (ZOA_ITSE)	3.448	1.367	0.505
FOPID (PS0_ITSE)	4.281	1.443	0.505
FOPID (ZOA_ITAE)	2.739	228.996ms	0.417
FOPID (PSO_ITAE)	3.726	172.806ms	0.075

Thus, from the result presented, the FOPID controllers outperforms the PID controllers with the PID designed using ZOA evaluated using the ITAE producing the best settling time of 2.739s, a rise time of 228.996ms, an overshoot of 0.417% and an undershoot of 1.990%. This indicates better damping and faster stabilization ability of the designed FOPID controller.

Figure 18 is a graph that shows the respective settling time of the deviation in frequency as achieved by the PID and FOPID controllers based on the error criteria employed for the optimization.

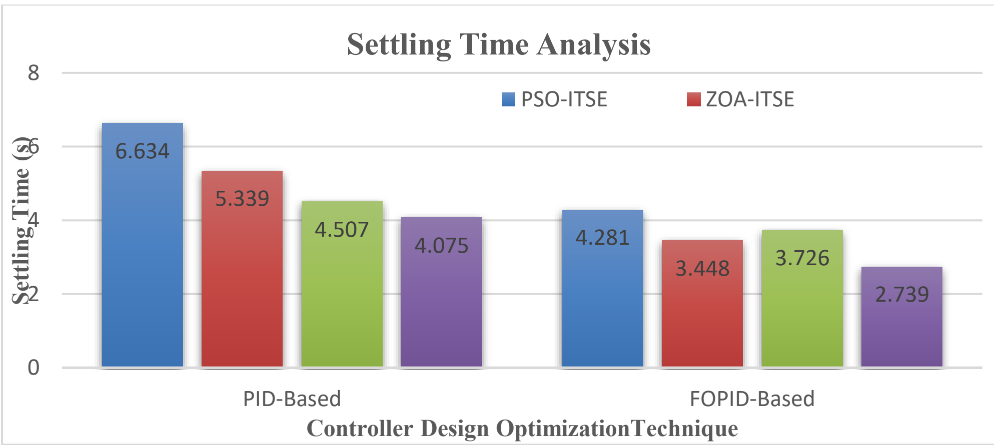

Figure 18: Frequency Deviation Settling Time

4.5 CONVERGENCE CURVE RESULT

The Convergence Curve in a Load Frequency Control (LFC) study typically represents the optimization algorithm's progress in minimizing the objective function; such as frequency deviation or control error) over iterations.

PSO converge at the 54 iterations. Optimization using the Zebra Optimization Algorithm (ZOA) produced a better optimization convergence as compared to the PSO based optimizations. The combined convergence curve is as represented in Figure19.

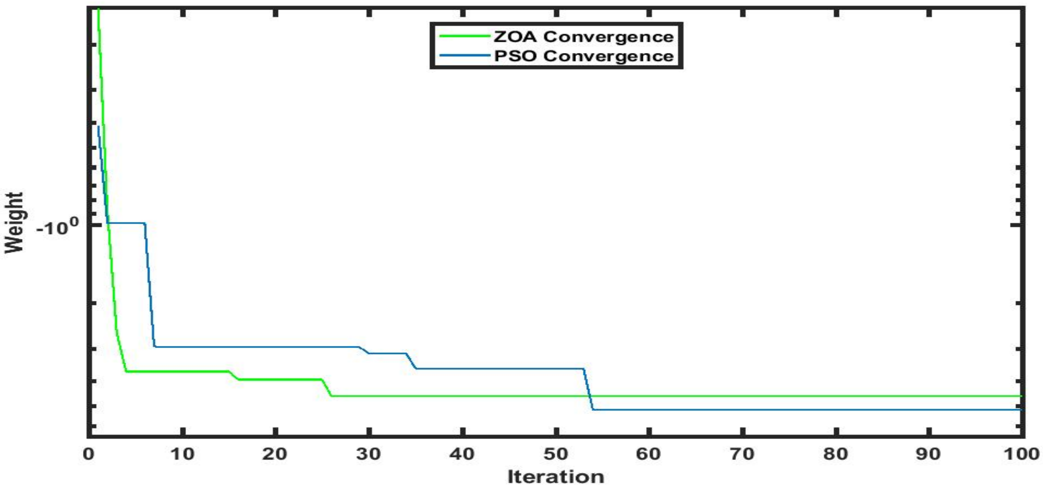

Figure. 19: Combined Convergence Curve

X DISCUSSION AND CONCLUSION

This study presented the design and simulation of an intelligent Fractional Order PID (FOPID) Load Frequency Controller optimized using the Zebra Optimization Algorithm (ZOA). The controller's performance was evaluated against a Particle Swarm Optimization (PSO)-based design to provide a comprehensive comparative analysis. The optimization objectives considered both ITAE and ITSE performance indices to assess dynamic response characteristics.

The simulation results clearly demonstrate the superiority of the ZOA-based design, particularly when evaluated using the ITAE criterion. The ZOA–ITAE controller achieved the shortest settling time of 2.739 s, outperforming all other configurations. In comparison, PSO–ITAE recorded a settling time of 3.448 s, representing a 20.56% increase. Similarly, PSO–ITSE exhibited a settling time of 4.281 s, which is 36.02% longer than ZOA–ITAE, while ZOA–ITSE settled at 3.726 s, corresponding to a 26.49% increase. These results confirm that the combination of ZOA and the ITAE objective function provides faster stabilization and superior damping performance.

Further analysis of the transient response parameters reinforces this conclusion. The ZOA–ITAE FOPID controller produced a rise time of 228.996 ms, an overshoot of 0.417%, and an undershoot of 1.990%. These values indicate improved damping characteristics and rapid system stabilization, which are critical requirements for maintaining load frequency stability in modern power systems.

In terms of optimization efficiency, ZOA also demonstrated a significantly faster convergence rate compared to PSO. The ZOA algorithm converged at the 26th iteration, whereas PSO required 54 iterations to reach convergence. This highlights the computational efficiency and robustness of ZOA in exploring the search space and identifying optimal controller parameters more rapidly.

A percentage-based performance comparison further emphasizes the effectiveness of ZOA–ITAE. Relative to this best-performing configuration, PSO–ITAE exhibits a 36.05% longer settling time, ZOA–ITSE shows a 25.89% increase, and PSO–ITSE demonstrates the poorest performance with a 56.32% longer settling time. These findings indicate that while ZOA-based tuning is generally effective, the choice of ITAE as the performance index is particularly crucial for achieving faster system stability.

Overall, the results obtained from this study confirm that the FOPID controller optimized using ZOA–ITAE provides the most efficient load frequency control performance among all tested configurations. The reduced settling time, minimal overshoot, faster rise time, and improved convergence characteristics make this approach highly suitable for enhancing frequency stability in interconnected power systems.

In conclusion, the integration of ZOA with an ITAE-based FOPID design offers a robust and computationally efficient solution for load frequency control problems. This approach is recommended for practical implementation in modern power systems where rapid stabilization, enhanced damping, and reliable optimization performance are essential.

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