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ANALYSIS OF CONTROL BASED MACHINE LEARNING BASED OPTIMIZATION TECHNIQUES FOR MULTI NETWORKS

Harpal Singh
System Analyst, Haryana Real Estate Regulatory Authority, Gurugram (Haryana), INDIA

Abstract: Artificial Intelligence (AI) represents a diverse field focused on creating machines that can perform tasks typically requiring human intelligence. At the core of AI lies machine learning (ML), a fundamental aspect enabling systems to learn and enhance their performance through experience rather than explicit programming. Amidst the array of tools in AI, machine learning stands out due to its capacity to identify patterns, make forecasts, and adapt to new information, ushering in a new era of intelligent systems. Artificial Neural Networks (ANN) fall under supervised learning and are inspired by the human brain's structure and functionality. ANNs comprise interconnected nodes organized into layers, including an input layer, one or more hidden layers, and an output layer. These networks are trained using labeled datasets to comprehend intricate patterns and relationships within the data. Optimization algorithms play a crucial role in refining machine learning models to achieve optimal performance. These algorithms aim to minimize or maximize an objective function representing the model's performance metric. Gradient descent, a foundational optimization technique, iteratively adjusts model parameters to minimize the error between predicted and actual outcomes. Other optimization tools, such as evolutionary algorithms, simulated annealing, and genetic algorithms, offer diverse approaches to finding optimal solutions within the expansive space of model parameters.

Keywords: AI, ANN, RNN, Load Frequency Control, Optimization

1. INTRODUCTION

The intersection of control-based methodologies and machine learning has opened new frontiers in optimizing interconnected networks, marking a significant leap in addressing the complexity and dynamism of modern network systems. This analysis focuses on the application of machine learning-driven control techniques tailored for multi-network environments. As networks expand in scale and heterogeneity, traditional optimization approaches struggle to meet the demands for efficiency, adaptability, and reliability. Leveraging machine learning in tandem with control strategies presents a promising avenue to navigate the intricate web of interdependent networks. Through a meticulous exploration of these integrated optimization techniques across multiple networks, this study aims to unravel the nuances, potential, and challenges inherent in this evolving paradigm, offering insights into enhancing network performance and resilience [1].

In the pursuit of enhancing network performance and scalability, the fusion of control-based mechanisms with machine learning algorithms has emerged as a transformative approach in managing interconnected networks. This analysis is dedicated to scrutinizing the realm of optimization techniques centered on control-based machine learning methods, specifically tailored for multi-network scenarios. The contemporary landscape of networks is characterized by their interconnectivity, varying protocols, and dynamic interactions, posing intricate challenges for traditional optimization strategies. By delving into the utilization of machine learning-driven control techniques in optimizing multiple networks, this examination seeks to uncover the efficacy, complexities, and potential advancements inherent in these innovative methodologies. Exploring this juncture provides a comprehensive understanding of how these techniques contribute to fortifying network infrastructures, fostering adaptability, and amplifying overall system performance [2].

2. REVIEW OF LITERATURE

The literature review spans various aspects of control-based machine learning optimization techniques for multi-network environments. Multiple studies investigate the application of machine learning algorithms, including deep reinforcement learning, adaptive control strategies, and distributed coordination mechanisms [3-10], emphasizing their efficacy in managing diverse interconnected networks. Additionally, discussions highlight the challenges posed by real-time implementation, scalability, and synchronization among disparate networks. These studies collectively underscore the growing significance of machine learning-driven control mechanisms in enhancing network efficiency, adaptability, and stability. They explore load balancing, stability maintenance, and resource allocation across interconnected networks, shedding light on the potential and limitations of these methodologies [11]. Overall, the reviewed literature accentuates the evolving landscape of optimization strategies tailored for multi-network scenarios, aiming to address the complexities and dynamics inherent in modern interconnected systems. The literature surrounding control-based machine learning optimization techniques for multi-networks showcases a dynamic evolution in addressing the complexities of interconnected systems. Traditional optimization approaches for multi-network environments have encountered limitations in managing the intricate interactions and dependencies among diverse networks [12-15]. Researchers have increasingly turned to machine learning, leveraging its adaptive capabilities, to enhance control-based methodologies for optimizing these interconnected systems. Studies highlight the potential of machine learning algorithms in learning patterns, predicting network behaviors, and dynamically adjusting control strategies, offering promising avenues to bolster the efficiency and adaptability of multi-network architectures.

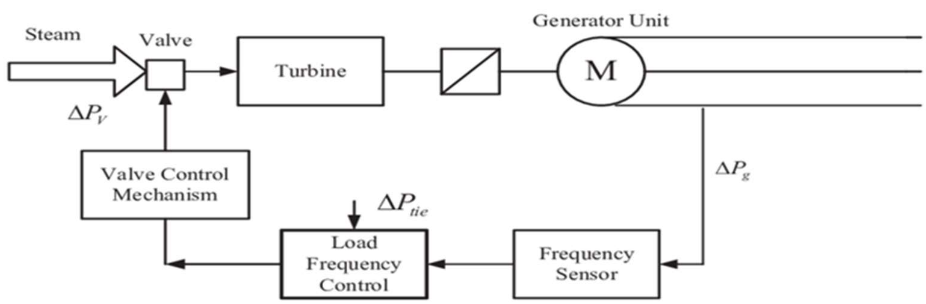
Moreover, the evolution of machine learning in network optimization has spurred a paradigm shift in how networks are managed and optimized. By harnessing the power of algorithms capable of learning from data and making informed decisions, researchers have explored novel ways to address the challenges posed by the dynamic nature of interconnected networks. Control strategies, integrated with machine learning techniques, have shown promising results in adapting to changing network conditions, mitigating disruptions, and maintaining stability across multiple networks. This amalgamation of control-based methodologies with machine learning algorithms signifies a transformative step toward more robust and adaptive optimization techniques for multi-network environments.

However, the literature also underscores certain challenges and gaps in the current landscape of control-based machine learning optimization for multi-networks. While machine learning algorithms exhibit adaptability, scalability, and predictive capabilities, their integration into control frameworks necessitates addressing issues related to interpretability, reliability, and real-time implementation. Additionally, achieving seamless coordination and synchronization among disparate networks remains a considerable challenge. Understanding and mitigating these challenges are crucial for the effective deployment of control-based machine learning techniques tailored for multi-network scenarios.

3. MACHINE LEARNING BASED OPTIMIZATION TECHNIQUES

3.1 Load Frequency Control

Load Frequency Control (LFC) stands as a critical mechanism within power systems, dedicated to maintaining the delicate balance between the power supply and demand, ensuring the stability and reliability of the electrical grid. In essence, LFC acts as the orchestrator, swiftly responding to fluctuations in power demand or unexpected disturbances within the grid. Its primary function involves swiftly correcting deviations in frequency caused by sudden changes in load or generation, guaranteeing that the system remains within acceptable frequency limits. By dynamically adjusting the power generation in response to these variations, LFC plays a pivotal role in averting grid instabilities, minimizing the risk of equipment damage, and preventing blackouts. This intricate control system operates in real-time, leveraging sophisticated algorithms and control strategies to swiftly counteract any deviations, thereby upholding the grid's operational integrity. Understanding LFC is crucial in comprehending how modern power systems manage and mitigate the effects of unforeseen disruptions, ensuring a stable and reliable supply of electricity [16].



Fgure1: Detailed LFC functional block representation

The restructuring of the power system demands significant changes in the power network, requiring active involvement from decentralized power utilities encompassing generation, transmission, and distribution. With escalating power needs and limited expansion of transmission lines due to socio-economic constraints, setting up high-capacity conventional power plants becomes challenging [17]. Consequently, power system operators face the ongoing task of balancing power demand by combining decentralized power generation facilities for the secure and reliable operation of the power grid. The principle of "one nation, one grid, one frequency," particularly observed in India, necessitates maintaining frequency stability at all times. However, the dynamic nature of the power system results in disturbances, faults, and abrupt shifts in load profiles, leading to perturbations that impact the frequency profile and, consequently, the entire grid. These disruptions can potentially cause fault transmission, equipment damage, and blackouts. To address these minor load perturbations, Load Frequency Control (LFC) is implemented. LFC regulates the power flow between interconnected grid areas through tie lines, swiftly correcting frequency deviations back to zero. Below in Figure 1 is a detailed block diagram illustrating the two areas of LFC.

3.2 Optimizing LFC Controller Gain

Optimizing the Load Frequency Control (LFC) controller gain involves fine-tuning a crucial parameter within the controller to enhance its performance in maintaining system stability. The controller gain represents the amplification factor applied to the error signal (the difference between the desired and actual frequency) to generate the control signal that adjusts power generation or flow within the system. The optimization process aims to find the most suitable value for this gain that minimizes frequency deviations, settling time, overshoot, or other performance metrics, ensuring a robust and stable system response. Through iterative adjustments and simulations, engineers explore various values of the controller gain to strike a balance between system stability and responsiveness [18]. Optimizing the LFC controller gain involves considering trade-offs. Higher gains may improve the controller's ability to quickly correct deviations but could lead to increased overshoot or oscillations. Lower gains might result in a more stable response but could lead to longer settling times or sluggish corrective actions. Optimizing the LFC controller gain involves finding the optimal value that maximizes system stability while minimizing the time and extent of deviations from the desired frequency, ensuring an efficient and reliable operation of the power system.

3.3 ANN Trained LFC Model

An Artificial Neural Network (ANN) trained Load Frequency Control (LFC) model involves leveraging neural network architectures to create a control system for managing and stabilizing power grid frequencies. In this context, an ANN is a computational model inspired by the human brain's structure and functioning. It consists of interconnected nodes, organized into layers (input, hidden, and output layers), which process information and learn patterns from data [19]. The ANN trained for LFC is designed to understand the complex relationships between various parameters affecting the power grid, such as load variations, power generation, and system disturbances. During the training phase, historical data on grid behavior, including frequency deviations and control actions taken, is used to teach the neural network how to predict the required corrective actions in response to different scenarios.

The training process involves adjusting the network's internal parameters (weights and biases) iteratively to minimize prediction errors. Once trained, the ANN-LFC model can take real-time input data from the power grid, such as frequency deviations, and predict the optimal control actions needed to maintain or restore the grid's stability. ANNs offer advantages such as adaptability to nonlinear relationships and the ability to learn from complex datasets. An ANN trained for LFC can potentially provide more accurate and efficient control decisions compared to traditional control approaches. However, designing and training an effective ANN-LFC model requires careful selection of network architecture, appropriate training algorithms, and high-quality training data representative of various grid conditions.

3.4 Optimized ANN LFC Model

An optimized Artificial Neural Network Load Frequency Control (ANN-LFC) model represents a refined and highly efficient system tailored to regulate power grid frequencies. This model undergoes a meticulous optimization process, starting with the selection of the most suitable ANN architecture, such as Feedforward Neural Networks (FNN) or Recurrent Neural Networks (RNN), carefully chosen to capture the intricate dynamics of the power grid. Additionally, the optimization involves selecting the most effective training algorithms. This includes exploring gradient descent-based methods, as well as heuristic algorithms such as evolutionary algorithms or swarm intelligence [20]. These choices significantly impact the model's learning speed, accuracy, and convergence, enhancing its capability to precisely predict and control frequency deviations. Moreover, the optimization process involves feature engineering to identify the most relevant input parameters that best characterize the power grid's behavior. These features enable the model to make accurate predictions and informed control decisions. Hyperparameter tuning becomes crucial in adjusting the internal settings of the neural network, such as learning rates, batch sizes, and activation functions, fine-tuning them to optimize the model's performance while preventing overfitting.

The optimized ANN-LFC model undergoes rigorous validation and testing across diverse datasets and real-time simulations. This ensures its reliability, accuracy, and robustness under various operating conditions and disturbances. The culmination of these optimization efforts results in an ANN-LFC model that delivers precise and rapid responses to frequency deviations. It effectively maintains grid stability by minimizing deviations and swiftly recovering from disturbances. The synergy between the refined neural network architecture, optimal training algorithms, and carefully curated input parameters empowers the model to efficiently regulate power grid frequencies, demonstrating superior performance in load frequency control scenarios.

4. RESULTS AND ANALYSIS

The identified problem refers to a specific benchmark challenge defined by the IEEE standard, focusing on a two-area system interconnected by a tie-line. This system operates on a shared 1000 MVA (mega-volt-ampere) power base, representing a standardized scale for power measurements within the system. The parameters essential for understanding and simulating this interconnected system are outlined in detail in Table 1, providing critical values and specifications related to various components such as transmission lines, generators, loads, and control elements. These parameters, serving as the foundation of the benchmark problem, encompass crucial details necessary for modeling and analyzing the behavior, performance, and interactions within the interconnected two-area system. They essentially form the groundwork for studies, simulations, and analyses aimed at evaluating control-based machine learning optimization techniques tailored specifically for this standardized scenario.

Table1: IEEE Two area benchmark parameters

Area	**1**	**2**
Speed regulation	R_1=0.05	R_2=0.0625
Frequency sensitive load coefficient	D*i=0.6*	D_2=0.9

Inertia Constant	H_1=5	H_2=4
Governor Time Constant	T_{g1}=0.2sec	T_{g2}=0.3sec
Turbine Time Constant	T_{t1}=0.5sec	T_{t2}=0.6sec

4.1 Conventional Controller

Figure 2, illustrates the frequency deviation observed when employing a conventional controller, serving as the baseline for all comparative analyses.

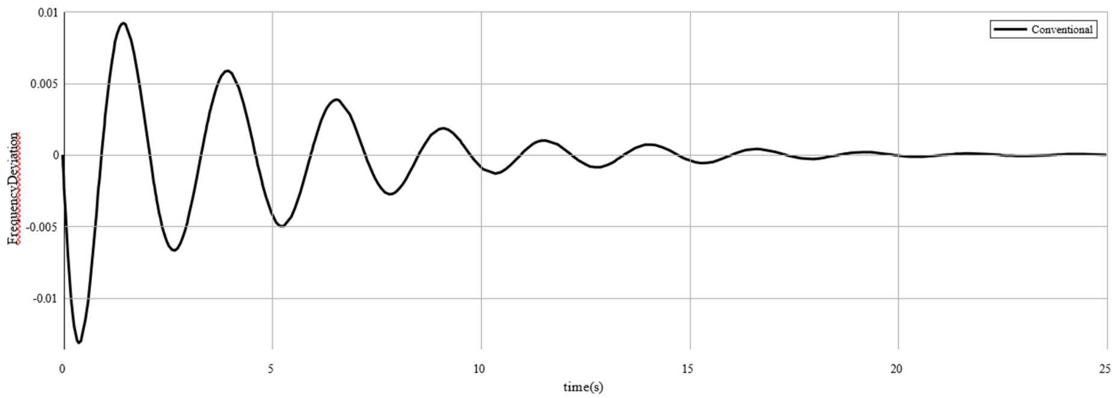


Figure 2: Frequency deviation of area1with conventional controller

The controller's performance metrics are highlighted, showcasing a settling time of 20.86 seconds, a minimum peak overshoot of 0.91%, and a peak time of 1.87 seconds. These metrics denote the controller's ability to regulate and stabilize frequency deviations within the system. They indicate the time required for the system to return to a stable state following disturbances, the extent to which the frequency surpasses its steady-state value before stabilizing, and the duration taken to reach this peak deviation. These benchmarks form a reference point against which the effectiveness of alternative control strategies, particularly those integrating machine learning optimization techniques, will be evaluated and compared.

4.2 Optimizing LFC Controller Gain

This statement discusses the comparison between the performance of different optimization algorithms, namely PSO (Particle Swarm Optimization), GWO (Grey Wolf Optimizer), SSA (Salp Swarm Algorithm), and WOA (Whale Optimization Algorithm), in conjunction with a benchmark controller. The assessment specifically focuses on their impact on settling the frequency deviation within the system. The findings, presented in Figure 3, display a comparison of how each optimization algorithm influences the system's frequency deviation settling time, peak overshoot, and peak time in response to disturbances. Among these algorithms, the GWO algorithm stands out for its superior performance. It demonstrates the shortest settling time of 4.2 seconds, indicating how quickly the system returns to a stable state after experiencing deviations. Additionally, GWO showcases the smallest peak overshoot of 0.46%, signifying minimal deviation from the desired frequency value, and a peak time of 1.22 seconds, denoting the time taken to reach this maximum deviation. These results suggest that among the assessed metaheuristic optimization algorithms, GWO exhibits the most efficient control over the system, offering a swift and precise response to disturbances. Its ability to minimize settling time, peak overshoot, and peak time implies a more stable and rapid recovery of the system from deviations, making it an optimal choice for enhancing the performance of the load frequency control system in regulating the power grid.

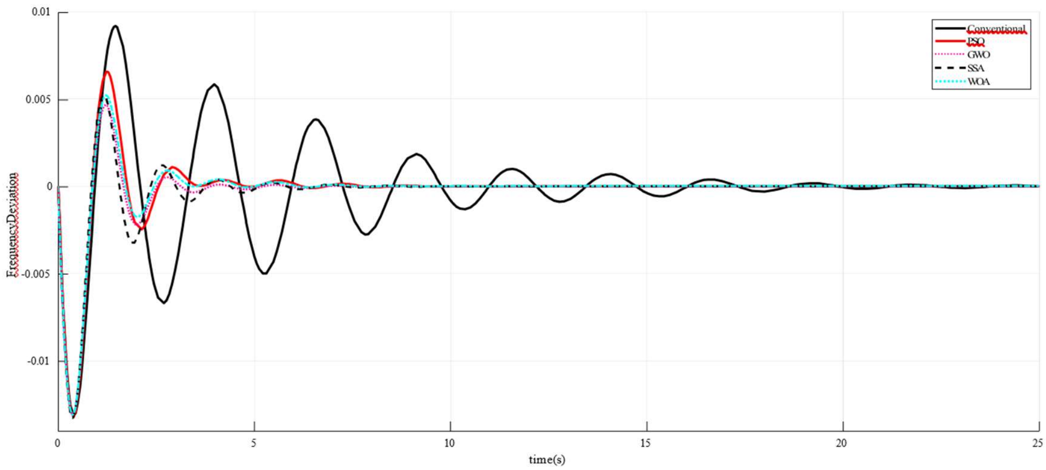


Figure 3: Comparative frequency deviationinarea-1for selected optimization algorithms

4.3 ANN Trained LFC Model

The results presented in figure 4, depict the performance comparison of different Artificial Neural Network (ANN) topologies using heuristic training algorithms within a MATLAB environment. The evaluation metrics used for comparison are peak overshoot and peak time, which are indicative of the ANN's ability to control and stabilize the system in response to disturbances. The analysis of the results suggests that among the considered ANN topologies, the Feedforward Backpropagation Neural Network (FNN) exhibits the most favorable performance. It demonstrates the lowest peak overshoot and peak time, indicating its superior ability to quickly restore system stability with minimal deviation from the desired frequency. Following FNN, the Linear Recurrent Neural Network (RNN) and Linear Train Neural Network (LNN) sequentially exhibit relatively good performances, albeit not as optimal as the FNN. Additionally, in evaluating the impact of training algorithms, it becomes apparent that heuristic training techniques outperform numerical optimization techniques in enhancing ANN performance for Load Frequency Control (LFC) (Figure 4).

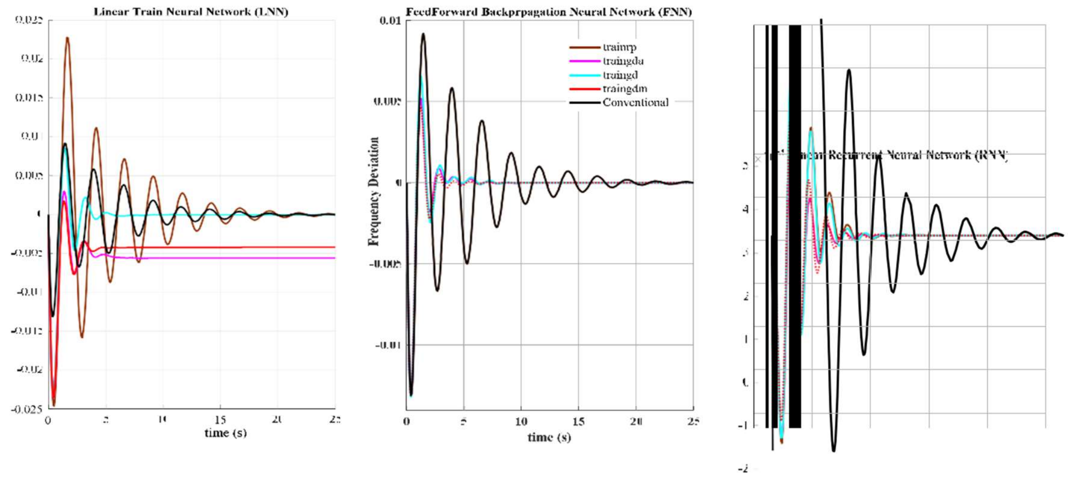


Figure 4: ANN topologies comparative performance with heuristic training techniques

4.4 Optimized ANN LFC Model

The results depicted in Figure 5 showcase the frequency deviation of the Feedforward Neural Network (FNN) based topology performance, specifically utilizing training data as the training algorithm. This representation highlights the effectiveness of FNN in managing frequency deviations within the power grid when compared to other neural network architectures, particularly the Recurrent Neural Network (RNN). The graphical representation in Figure 5 illustrates how the FNN-based topology outperforms the RNN topology in terms of controlling frequency deviations within the power grid. The FNN-based model demonstrates superior performance, showcasing reduced frequency deviations and more precise control actions compared to the RNN topology. This outcome suggests that the FNN architecture, when paired with training data as the training algorithm, is more adept at regulating and stabilizing the power grid's frequency responses.

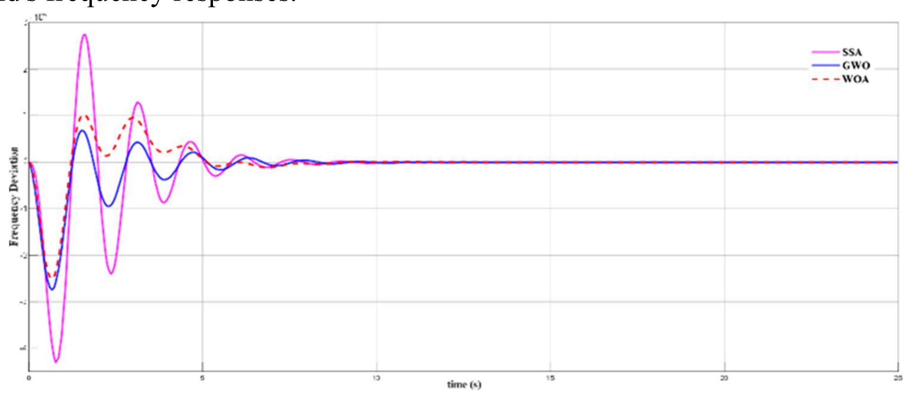


Figure 5: Comparative optimized FNN based frequency deviation

The table 2 presents a comparative analysis of the performance metrics for Feedforward Neural Network (FNN) and Recurrent Neural Network (RNN) architectures using different optimization algorithms in Load Frequency Control (LFC) systems. The evaluated metrics include peak time (tp in seconds), settling time (ts in seconds), and maximum peak overshoot (Mp in percentage) for each architecture and optimization algorithm pair. Across the various optimization algorithms studied—Salp Swarm Algorithm (SSA), Whale Optimization Algorithm (WOA), and Grey Wolf Optimizer (GWO)—the FNN consistently demonstrates competitive or superior performance compared to the RNN. Specifically, when employing the SSA algorithm, the FNN architecture achieves a peak time of 1.62 seconds, while the RNN registers a slightly lower peak time of 1.2 seconds.

Table 2: Overall optimized ANN model performance comparison hart

	tp (s)		ts(s)		Mp (%)	
	FNN	**RNN**	**FNN**	**RNN**	**FNN**	**RNN**
SSA	1.62	1.2	7.09	7.57	0.27	0.96
WOA	1.59	1.18	4.96	5.7	0.10	0.50
GWO	1.53	1.18	6.3	8.49	0.06	0.70

This trend continues across the other algorithms, highlighting the FNN's generally quicker response in reaching the peak deviation compared to the RNN. Regarding settling time, the FNN architecture consistently shows either comparable or faster settling times compared to the RNN for all optimization algorithms. For instance, under the WOA algorithm, the FNN achieves a settling time of 4.96 seconds, slightly outperforming the RNN's 5.7 seconds. Similar trends are observed across the SSA and GWO algorithms, suggesting the FNN's tendency to converge faster towards the desired frequency range after a disturbance. In terms of maximum peak overshoot, the FNN generally exhibits lower overshoot percentages compared to the RNN across all optimization algorithms. For instance, with the GWO algorithm, the FNN demonstrates a notably lower overshoot of 0.06%, while the RNN records a higher overshoot of 0.70%. This trend implies that the FNN architecture tends to achieve more precise control over frequency deviations, minimizing the extent of overshoot from the desired frequency value compared to the RNN. Overall, the results indicate that, across various optimization algorithms, the FNN architecture consistently showcases favorable performance metrics—quicker peak times, faster settling times, and reduced peak overshoot—compared to the RNN in Load Frequency Control systems. This suggests the potential superiority of the FNN architecture in regulating power grid frequencies and maintaining stability, making it a more promising choice for LFC applications when considering these evaluated performance metrics. The table 3 presents a comprehensive comparison of performance metrics across different optimization algorithms and neural network architectures within Load Frequency Control (LFC) systems. Each algorithm-architecture combination reveals distinct characteristics in managing frequency deviations and maintaining stability within power grids.

Table 3: Comparative analysis of GWO, RNN and WOA-FNN

	Peak Time tp (s)	**Settling Time ts (s)**	**Peak Overshoot Mp (%)**
GWO	1.22	4.2	0.46

RNN	1.71	5.7	0.23
WOA-FNN	1.59	4.96	0.10

Firstly, the GWO algorithm, combined with an unspecified neural network architecture, showcases efficient control capabilities with a notably short Peak Time of 1.22 seconds, indicating a rapid response to disturbances. Its Settling Time of 4.2 seconds suggests quick convergence to the desired frequency range, while the moderate Peak Overshoot of 0.46% implies controlled deviation from the target frequency, ensuring stability without significant overshoot. Secondly, the RNN architecture employing the training data algorithm exhibits precision and accuracy in frequency regulation. Despite a slightly longer Peak Time of 1.71 seconds, the system demonstrates a commendably low Peak Overshoot of 0.23%, showcasing the ability to swiftly stabilize the grid without deviating substantially from the desired frequency. The Settling Time of 5.7 seconds indicates a steady convergence to the target range, emphasizing precision even with a longer response time.

5. CONCLUSION

The study offered a comprehensive understanding of how optimization techniques and chosen neural network architectures, key components in Machine Learning (ML) methodologies, interact within a specific application context. In this research, the focus was on multi-area Load Frequency Control (LFC), serving as a litmus test for evaluating and validating the selected ML techniques. The study aimed to establish a robust framework for optimizing techniques, particularly highlighting their effectiveness in fine-tuning the parameters of LFC's PI controllers. Among the various metaheuristic optimization methods, the GWO algorithm stood out, demonstrating superior performance in adjusting PI control parameters for LFC systems. Its efficacy in meeting convergence and settling time objectives was evident, establishing its significance in enhancing control mechanisms. Moreover, the study aimed to create an optimized ANN model functioning as a secondary LFC controller. Within this scope, the WOA algorithm demonstrated remarkable effectiveness in optimizing the weights and biases of the FNN, highlighting its potential to enhance the learning capabilities of neural networks in LFC systems. This emphasized the significance of leveraging optimization algorithms to refine neural network models, potentially improving their efficacy as secondary LFC controllers.

References

[1] Dipayan Guha,Provas Kumar Roy, Subrata Banerjee, "Load frequency control of large scale power system using quasi-oppositional grey wolf optimization algorithm" InternationalJournalofEngineeringScienceandTechnology,vol.19,no.4,pp. 1693-1713, 2016.

[2] A. Fathy and A. G. Alharbi, "Recent Approach Based Movable Damped Wave Algorithm for Designing Fractional-Order PID Load Frequency Control Installed in Multi-Interconnected Plants with Renewable Energy," in IEEE Access, vol. 9, pp. 71072-71089, 2021.

[3] H. R. Madvar, M. Dehghani, R. Memarzadeh, E. Salwana, A. Mosavi and S. S., "DerivationofOptimizedEquationsforEstimationofDispersionCoefficientin Natural Streams Using Hybridized ANN With PSO and CSO Algorithms," in IEEE Access, vol. 8, pp. 156582-156599, 2020.

[4] S.Mirjalili, S.M.Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” Adv Eng Softw, vol. 69, p. 46, 2014.

[5] Neelamsetti, Kiran & Indragandhi, V., “Analysis on various optimization techniques used for Load Frequency Control in power system” vol. 15, pp. 249-273, 2018.

[6] V. Gholamrezaie, M. G. Dozein, H. Monsef and B. Wu, "An Optimal Frequency Control Method Through a Dynamic Load Frequency Control (LFC) Model Incorporating Wind Farm, "in IEEE Systems Journal, vol.12, no.1, pp.392-401, 2018.

[7] Y. Xu, C. Li, Z. Wang, N. Zhang and B. Peng, "Load Frequency Control of a Novel Renewable Energy Integrated Micro-Grid Containing Pumped Hydropower Energy Storage," in IEEE Access, vol. 6, pp. 29067-29077, 2018.

[8] Y.Zhangand, T.Yang,"Decentralized Switching Control Strategy for Load Frequency Controlling Multi-Area Power Systems With Time Delay and Packet Losses," in IEEE Access, vol. 8, pp. 15838-15850, 2020.

[9] H. Bevrani and P. R. Daneshmand, "Fuzzy Logic-Based Load-Frequency Control Concerning High Penetration of Wind Turbines," in IEEE Systems Journal, vol. 6, no.1, pp. 173-180, 2012.

[10] H. A. Yousef, K. AL-Kharusi, M. H. Albadi and N. Hosseinzadeh, "Load Frequency Control of a Multi-Area Power System: An Adaptive Fuzzy Logic Approach," in IEEE Transactions on Power Systems, vol. 29, no. 4, pp. 1822-1830, 2014.

[11] N.E.Y. Kouba, M. Menaa, M.Hasniand M.Boudour,"LFC enhancement concerning large wind power integration using new optimized PID controller and RFBs," in IET Generation, Transmission & Distribution, vol. 10, no. 16, pp. 4065-4077, 2016.

[12] I. Nasiruddin, G. Sharma, K. R. Niazi and R. C. Bansal, "Non-linear recurrent ANN-based LFC design considering the new structures of Q matrix," in IET Generation, Transmission & Distribution, vol. 11, no. 11, pp. 2862-2870, 2017.

[13] X. Wang, Q. Zhao, B. He, Y. Wang, J. Yang and X. Pan, "Load frequency control in multiple micro grids based on model predictive control with communication delay," in The Journal of Engineering, vol. 2017, no. 13, pp. 1851-1856, 2017.

[14] Z. Yan and Y. Xu, "Data-Driven Load Frequency Control for Stochastic Power Systems: A Deep Re-enforcement Learning Method with Continuous Action Search," in IEEE Transactions on Power Systems, vol. 34, no. 2, pp. 1653-1656, 2019.

[15] C. Osinski, G. Villar Leandro and G. H. da Costa Oliveira, "Fuzzy PID Controller Design for LFC in Electric Power Systems, "in IEEEL America Transactions, vol. 17, no. 01, pp. 147-154, 2019.

[16] J. Yang, X. Sun, K. Liao, Z. He and L. Cai, "Model predictive control-based load frequency control for power systems with wind-turbine generators," in IET Renewable Power Generation, vol. 13, no. 15, pp. 2871-2879, 2019.

[17] D. Zhou, Z. Quan and Y. Li, "Hybrid Model Predictive Control of ANPC Converters with Decoupled Low-Frequency and High-Frequency Cells, "in IEEE Transactions on Power Electronics, vol. 35, no. 8, pp. 8569-8580, 2020.
[18] D.Yang etal.,"Inertia-adaptivemodelpredictivecontrol-basedloadfrequency control for interconnected power systems with wind power," in IET Generation, Transmission & Distribution, vol. 14, no. 22, pp. 5029-5036,2020.
[19] H. Haes Alhelou, M. E. Hamedani Golshan and N. D. Hatziargyriou, "Deterministic Dynamic State Estimation-Based Optimal LFC for Interconnected Power Systems Using Unknown Input Observer, " in IEEE Transactions on Smart Grid, vol.11, no.2, pp.1582-1592,2020.
[20] H.Chen, R.Ye, X.Wangand R.Lu, "Cooperative Control of Power System Load and Frequency by Using Differential Games," in IEEE Transactions on Control Systems Technology, vol. 23, no. 3, pp. 882-897, 2015.