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Optimizing Artificial Neural Networks for Multi Area Network : A Metaheuristic Perspective

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Abstract: Regression, data classification and function approximation are among the most common applications that make use of machine learning models. However, due to the vast range of applications for machine learning, comprehensive understanding of how to choose a model based on machine learning, as well as how to choose its structure, training method, and performance analysis criterion, is frequently lacking. This key issue is addressed using a well-known load frequency control (LFC) problem which is instrumental in maintaining balance between power generation and load demand. The study relates to developing and contrasting the performance of the Meta heuristic optimization based approach to the artificial neural network (ANN) based machine learning topology for the LFC control against the optimized ANN controller. The selected performance indices are peak time and settling time of the frequency deviation. It is observed that Linear Neural Network (LNN) outperforms Feedforward Neural Network (FNN) and Recurrent Neural Network (RNN). The performance is enhanced when its parameters are optimized by the metaheuristic algorithms.

Keywords: load frequency control; machine learning; artificial neural network, optimization; metaheuristic algorithm; frequency deviation

I. INTRODUCTION

The balance between electrical generation and consumption must be maintained in order to keep the power system stable, and this is where load frequency control (LFC) comes into play. As it works to match on-demand power demand with on-demand power generation. This aspect of power system is very much essential for the dependable and effective operation of electrical grids. Within a constrained tolerance band, which is often 50 Hz or 60 Hz depending on the region, LFC aims to maintain a steady grid frequency. Any variation from this frequency can have detrimental effects, such as causing equipment damage, blackouts, or even the collapse of the entire grid.

Power system dynamics can be quite complicated and non-linear, depending on a number of variables, including load variations, generation fluctuations, and disturbances. Numerous traditional control-based strategies have been put forth in the literature [1–5] to offer control in the load frequency control loop and to control the frequency against the aforementioned ways. Linear controllers mostly employed in any combinational form of Proportional-Integral-Derivative controller are commonly used in Load Frequency Control (LFC) systems for maintaining grid frequency within an acceptable range. However, they e some disadvantages and limitation including limited accuracy for complex system, inadequate adaptability to system configuration or structural change and load perturbations, lack of predictive capability, slow response to frequency deviations tuning challenges are among the prominent ones.

Modern LFC systems frequently take into account more sophisticated control approaches involving Artificial Neural Netwrok based machine learning [6-33]. The ANN based control gives advantage of nonlinear system modeling of a power network, adaptability and predictability to variable operating conditions and grid conditions. Bur they too have shown limited capability in a way that they are data driven, are prone to over fitting, requirement of complex training and tuning and above all have the generalization issue.

Researchers have also employed various optimization algorithms in Load Frequency Control (LFC) of power systems with the objective of enhancing the system's ability to maintain grid frequency within acceptable limits while optimizing various operational objectives they enable efficient generation and reserve allocation, integrate renewable energy, manage constraints, and adapt in real-time, ultimately ensuring the reliable and economic operation of power systems [34-43]. Different types of algorithms based on swarm intelligence, evolutionary premised , hybrid or memetic approach have been applied to the LFC problem. They offer wide applicability owing to inherent advantages of enhanced efficiency and adaptability, multi-objective optimization under wide range of constraint handling, coupled with predictive inheritance feature . But they too are marred with the limitation of different types of search area ability, high computational time, sensitivity to model inaccuracies, extrapolation and exploration uncertainties

Based on this there is a dire need to develop a hybrid approach which is capable of providing improved modeling accuracy with improved control performance which can effectively handle power system non linearities.

In this paper a hybrid approach is presented. The first section has explained the need for hybrid approach. The second gives a brief account of the load frequency control problem. The third section explains the development of the optimized followed by the results and discussion in the penultimate section. The conclusion is drawn in the last section.

II. LOAD FREQUENCY CONTROL SYSTEM

This section is divided in two subsections. The first subsection gives the brief insight of the LFC control problem and the subsequent sub section gives the benchmark model for employed for validation of the proposed system.

A. A Brief Overview : Load Frequency Control

The stability, dependability, and effective operation of electrical grids are all dependent on load frequency control (LFC) hence it a crucial part of the power system. LFC involves grasping the technology and control systems that underpin the seamless delivery of electricity to consumers while adapting to ever-changing demands. LFC is designed to maintain the balance between the electrical generation and consumption of electricity. It is crucial in keeping the frequency to the predefined standard value. Any deviation from the standard value also known as the target value in LFC can lead to equipment damage leading to cascading blackout and eventually the blackouts. The key components of the load frequency control are the generator and their associated control mechanism of turbine-governor control. All this together forms the primary frequency controller (PFC). The PFC reacts to sudden small changes in load and accordingly control the generation thus matching the load demand. Every conventional generator is usually equipped with PFC. The generators forms the heart of the electricity production. This may include single source or can house multiple sources of power generation which may be thermal, hydro, nuclear or renewable energy based. The PFC can be for single area housing multiple generators catering to the dedicated load demand. But power systems are large interconnected system and hence are divided in large areas. These multiple areas are connected to each other through the tie line. Here comes the secondary frequency controller (SFC) which involves a tie line controller with functional PI controller in each area connected to the two area. The SFC is in charge of adjusting frequency discrepancies that continue after PFC has taken action. It exercises the power flow control between the connected area so as to bring the frequency deviation to zero. The efficacy of the controller is measures in terms of settling the frequency deviation in either or interconnected areas which are measured in terms of peak overshoot and settling time of the frequency deviation.
The generalized block diagram is shown in fig. 1 below:

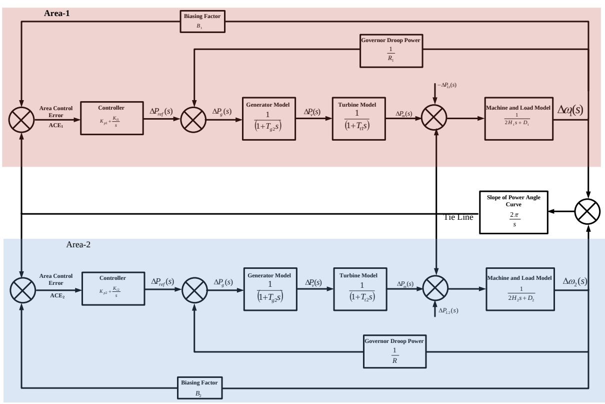

Figure 1. Benchmark Two Area LFC Model[44]

Since load requirements are dynamic in nature so the electric power has to be scheduled in such a way that it meets the load requirements and the associated losses [15]. Mathematically at any instant (1) has to be followed

$$\sum P_{generation} = \sum P_{load\ demand} + \sum P_{losses} \quad (1)$$

Time Integral of Absolute Error (ITAE), which is based on the frequency deviation of both the interconnected areas along with the deviation in tie line power is one of the frequently used objective functions for getting the control parameters of LFC. It is formulated as

$$J = \int \left(|\Delta f_1| + |\Delta f_2| + |\Delta P_{12}| \right) dt \quad (2)$$

B. Benchmark Two Area Load Frequency Control

A generalized LFC model has been explained in the preceding sub section. Figure 1 is the representation of the tqo area benchmark control problem [44]. Each area has a turbine governor control with time constant represented as Tti and Tgi, A conventional generator with, inertia constant Hi droop controller with gain Ri and frequency dependent load Di ,a conventional PI controller with proportional gain Ki and integral gain Ki.

The two area benchmark system and controller parameters are given in in Table 1 below:

Table I. Benchmark LFC model parameters

T_{t1}	0. 5 s	R_1	0.05
T_{t2}	0.6 s	R_2	0.0625
T_{g1}	0.2 s	K_{p1}	0.97
T_{g2}	0.3 s	K_{p2}	0.97
H_1	5 sW/VA	K_{i1}	0.37
H_2	4 sW/VA	K_{i2}	0.37
D_1	0.6	Ps	2.0
D_2	0.9	ΔP_L	0.1875 p.u.

III. DEVELOPMENT OF OPTIMZED ANN TOPOLOGY

This section describes the methodology for the development of optimized ANN topology for the control of multiarea load frequency problem. This section is divided in three subsections. Fist subsection explains the selection of metaheuristic optimization algorithm for the selected benchmark problem [45]. This section gives the brief insight of the selection procedure and the methodology adopted. The choice of ANN topology is explained in the second subsection [46]. The selection process and the methodology used are briefly explained in this section. Based on the selected optimized algorithm and the selected ANN toplogy a hybrid optimized ANN model development is explained in the third section.

A. Selection of metaheuristic optimization algorithm for LFC

Researchers and practitioners routinely adapt and employ metaheuristic algorithms to solve difficult real-world optimization issues in a variety of fields. They are general-purpose methods that are independent of specific issue models and can be applied to a wide range of optimization situations. These methods are designed to identify approximations when finding an exact solution is computationally unfeasible or when dealing with non-convex, high-dimensional, or combinatorial optimization problems. Metaheuristic algorithms are generally classified into several categories based on their underlying principles, search strategies, and inspiration sources. Figure 2 give one way of classifying the metaheuristic algorithm while mentioning the widely used and popular optimizing algorithms.

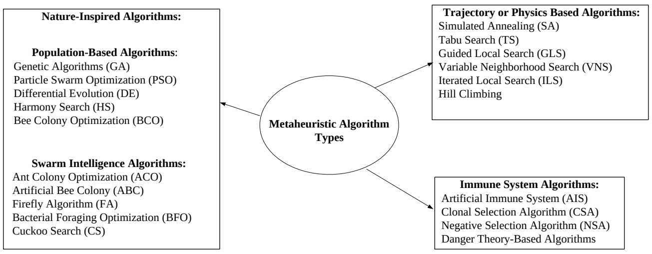

Figure 2. Broad classification of metaheuristc algorthm

The pool of these algorithms is quite wide and deep, so is the way of classifying them fig. 2 is just a glimpse of the same. Another way can be based on selection of search space, nuumber of agents involved, local or global search. The way of considering an alogrithm can have different combinations like GA fall under nature inspired algorithm, is also a type of polulaation based algorthm, does come under bio inspired classification and is alo a type of probalistic algorithm.

The selection of particular optimization algorithm depends on the kind of optimization problem, its characteristics, and how well the algorithm fits the particular task at hand. Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA) are selected based upon their unique characteristics. To start, they all use population-based methods that iterate over time to get the greatest results. Second, these algorithms strike a balance between exploitation and exploration. Thirdly, they preserve population variety by delaying the emergence of subpar solutions [47].

The controller parameters of the LFC model as shown in fig 1 whose parameters are given in table 1 are tuned using the four selected algorithm i.e. PSO, SSA, GWO and WOA. The whole procedure and obtained parameters is described in [45]. The obtained simulation results are reproduced without the loss of generality and are shown in fig. 3 below.

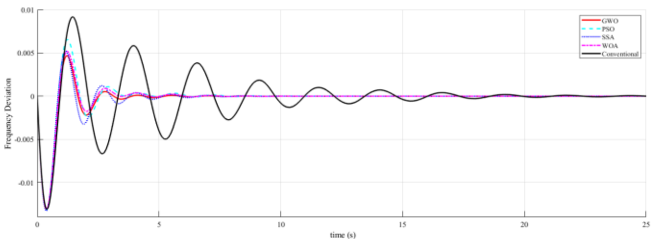

Figure 3. Compartive frquency deviation of area 1 using optimzation LFC

From the obtained results on the basis of peak time, peak overshoot and settling time it is observed that the performance of GWO and WOA are nearly at par with peaksettling time of 1.22 s but different peak overshoot of 0.46% and 0.51% with setting time of 4.2 s and 5.9 s respectively.

B. *Selection of ANN toplogy for LFC*

Artificial Neural Network (ANN) is a key concept in the field of artificial intelligence and machine learning. ANN is a computational model that is inspired by the form and operation of biological neural networks, such as the human brain. An ANN is made up of interconnected nodes arranged in layers that are perceptron-like artificial neurons. A variety of computing tasks, including as pattern recognition, classification, regression, and decision-making, are performed with ANNs.[48,49]

The key components of ANN are the input layer, hidden layer, output layer. Input layer is where the data is fed into the system where each neuron represents a feature or an attribute of the data. Hidden layer is where generally the data is processed and transformed between the input and the output layer. This happens through a series of weighted neuron connection along with biases and activation. The final output in form of user defined form of prediction, classification, or functional approximation is obtained from the output layer.

A neural network's artificial neurons and connections are arranged in a specific way according to a ANN topology. The capabilities of the network and its suitability for particular activities are greatly influenced by these topologies. Figure 4 give the categorical classification of different ANN topologies

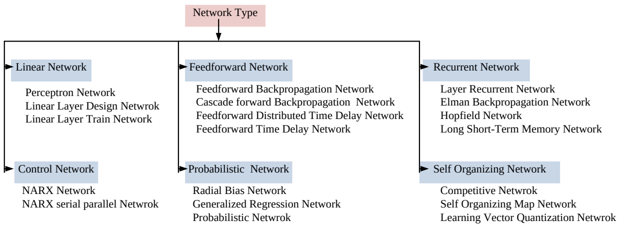

Figure 4. Common ANN topologies

Linear network, often known as a multilayer Perceptron, are typically used for natural language processing, audio recognition, and image recognition. Data in a feedforward neural network moves from the input layer to the output layer in a single direction. Neither cycles nor feedback loops exist. These are typically used for function approximation, regression, classification, and pattern recognition. The order of the input is important when using recurrent neural networks (RNNs), which are intended for sequential data. They are able to preserve internal state or memory thanks to recurrent connections and are useful in natural language processing, time series analysis, and speech recognition. In order to understand and forecast the behavior of dynamic systems, the Nonlinear AutoRegressive Moving Average with eXogenous Inputs (NARX) model is a form of time series model utilized in many disciplines, including engineering, economics, and machine learning. By adding exogenous inputs, the NARX model expands the conventional AutoRegressive Moving Average (ARMA) model, making it better suited for simulating complex systems with outside influences. A particular kind of artificial neural network that excels in tasks like function approximation, classification, and clustering is the Radial Basis Function (RBF) Neural Network. Radial basis functions are used as the network's activation functions, which distinguishes RBF networks from other types of networks. Self-organizing networks are unsupervised learning networks that are used for visualization and clustering [49]

Based on the review of literature the selected ANN topologies are Linear Neural Network (LNN), Feedforward Neural Network (FNN) and Recurrent Neural Network (RNN). The whole comprehensive selection procedure is taken is refereed from [46]. The heuristic approach of training using traingd is adopted. The benchmark model described in II.B is used where the controller is replaced by the selected ANN topologies.

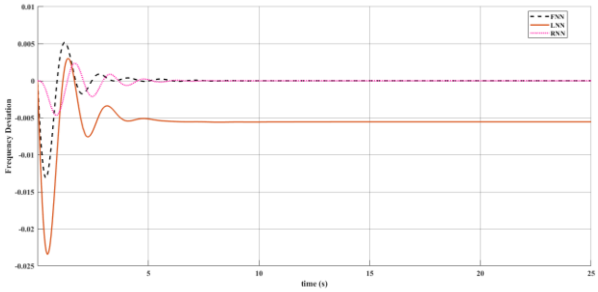

Figure 5. Comparative frequency deviation of area 1 of selected ANN toplogies

For the FNN, LNN and RNN the peak time is 1.26 s, 1.41 s and 1.71 s respectively while the settling time is 7.4 s, 6,9 s and 7.3 s respectively. LNN performs better in terms of settling the frequency deviation at the earliest.

C. *Optimized ANN Model for LFC*

Form the above two subsection it is evident WOA and GWO are the front runners in the optimized algorithm selection based on the selected performance indices of peak time and settling time. While, for the ANN topologies the LNN topologies performs the best. As it is now clear that ANN based models performs better than the optimization algorithm in settling the frequency deviation with comparatively lower peak overshoot and faster settling time. But still in quest for the better performance of the LFC using a hybrid approach this subsection explains the methodology of having a GWO based LNN topology for the selected benchmark LFC model.

For optimization of the ANN topology there are many parameters like optimizing the weight matrices, biases, activation function, learning rate, weight initialization, optimizing the learning algorithm, defining the iteration stopping criterion to mention the few. In the current case weights and biases of the LNN network are optimized. The process of obtaining and implementing then same is represented with the help of process flow diagram as shown in fig. 6 below.

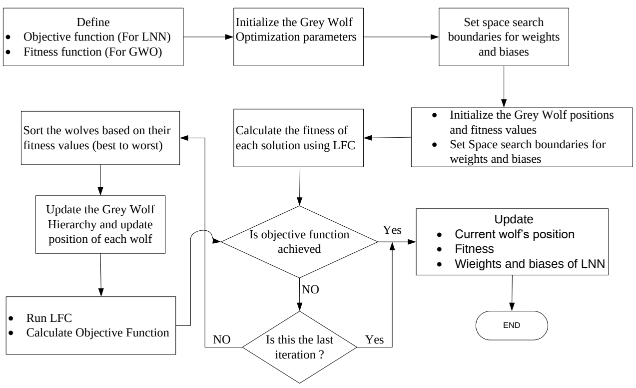

Figure 6. Algorithm for GWO tuned LNN

IV. Results and Discussion

The selected two area benchmark controller as explained in II. B is employed for the validation of the developed optimized ANN topology. In this case LNN is optimized using GWO and WOA. The controller shown in fig. 1 in both the areas are replaced by the developed optimized LNN controller and the performance is gauged for the load perturbation of 0.1875 p.u. The frequency deviation of area 1 when controlled separately by GWO and WOA tuned LNN network is shown in fig 7.

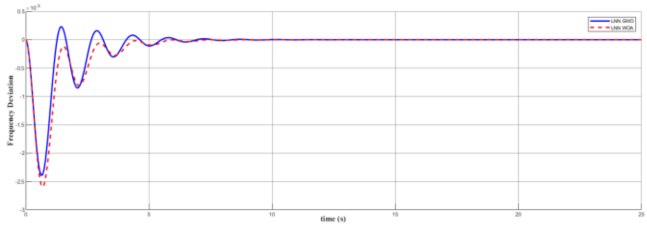

Figure 7. Comparative frequency devaiation of area 1 of optimized RNN

The peak time for GWO tuned LNN is 1.41s in comparison to 1.47s for WOA tuned LNN where the respective setting time is 3.9 s against 4.1s. Thus GWO tuned LNN network performs better in controlling the dynamics of the selected benchmark two area network. The performance is better than the earlier developed optimization based conventional controller and the conventional LNN controller as discussed in III.A and III.B

V. Conclusion

This paper presented a systematic methodology of developing an optimized artificial neural network (ANN) based machine learning topology for a benchmark two load frequency control area control (LFC). The study was conducted in three phases namely selection of best performing optimization algorithm, selection of best performing ANN topology and lastly development of the optimized ANN topology for the selcetd LFC problem. From the obtained results it was observed that Grey Wolf Optimization GWO based Linear Neural Network (LNN) outperformed the performance of the individually applied optimization algorithms and ANN topologies respectively.

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