IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Machine Learning Taxonomy for Multi Area Network Control

[1]Shelja and [2]Pawan Kumar

[1]Research Scholar,[2]Associate Professor
[1,2]Department of Computer Science and Application
[1]NIILM University, Kaithal, India

Abstract : Machine learning have an inherent attribute of learning from the data which may be numerical data or categorical data in order to imitate human intelligence for increasing the performance of the system. All this is attributed to the availability of different types of machine learning algorithm Each type of machine learning model has its strengths and weaknesses, and the choice of model depends on the nature of the data and the specific problem at hand. So generalization is always worked upon for the selection of the machine learning model. In this paper, authors have systematically developed a framework for machine learning based control for a very practical problem of supply-load balance as applicable to electrical power system. The identified problem is regression based. The paper thoroughly analyzes different combinations of machine learning algorithm along with different network architecture for achieving the desired results in the selected multi-area load frequency control problem with greater accuracy and high speed.

***IndexTerms* - Machine learning, network type, training technique, load frequency control, Mutli area control**

I. INTRODUCTION

In the past decade the world has witnessed tremendous technological growth owing to Artificial intelligence and most recently machine learning has contributed tremendously towards the betterment of global civilization. Machine learning focuses on using data and algorithm to simulate the human behaviors and that too with progressively increasing accuracy. Algorithms are developed and trained to employ statistical approach for performing either or both classification and predication for revealing data mining initiatives. Such insights are invariably employed in almost every walk of life viz. health care, sentiment analysis, neural information processing, marketing and the social sciences, bioinformatics, robotics, market analysis, electrical power system, space science, defense, surveillance to name the prominent few [1-8].

The wide field of machine learning includes artificial neural networks (ANN) and deep learning. ANN has the sophisticated capacity to ingest and process data in a way that substantially lowers the need for human involvement for adaptability to handle real-time problems involving large and complex data. Hence, ANN ranks among the best available means for performing complex operation of pattern classification [9-11] and function approximation [12-14].

The generalized work process of designing and implementing an artificial neural network involves three major steps. Starting with the data preparation for the ANN network followed by defining the ANN network which involving creating a particular type of network out of available number of network, configuring the network object and then initializing the weights and bias of the network. The last step is training and applying the ANN network which involves complex intrinsic steps of selecting the performance function, training algorithm, selecting the network performance criterion, analyzing and reconfiguring the network.
But the implementation of the ANN based machine learning method has its own challenges, owing to the different types of real world problem categorized to classification, prediction or control.

This paper particular highlight the ANN based machine learning taxonomy as applicable to selected load frequency control problem in power system.

1.1 Review on Machine Learning Based Load Frequency Control

Electric power systems are interconnected systems which are always required to meet the ever growing consumer electric power demand without compromising both the quality and reliability of the supplied power. This operation becomes even more complex under the constraints of (a) less dependency on fossil fuel based power owing to exhaustible nature of the fuel and growing environmental concerns, (b) growing penetration of renewable energy resources for economic operation because of inexpensive and inexhaustible nature of the fuel like wind and solar and (c) more stressed transmission line which are made to operate near thermal limits due to socio-economic constraints on expanding transmission network [6].

Interconnected system comprising of areas or regions are required to maintain balance between supply (electric power) and demand (load). A sample two area network connected through a tie-line is shown in fig. 1.

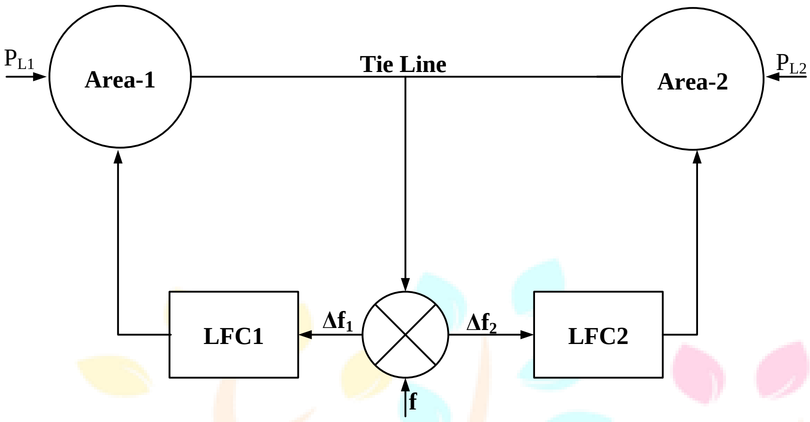

Figure 1: A general representation of two Area LFC

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

$$\sum P_{generation} = \sum P_{demand} + \sum P_{losses} \tag{1}$$

The key performance parameter being the frequency which has to be maintained at fixed value. A small perturbation in (1) results in the shift in operating point and the same is reflected in the frequency deviation. So load frequency control (LFC) which earlier addressed the dispatching problem [16] with the help of fixed gain controller is now considered to be an optimization problem where the gains of the controllers have to optimally selected so as to enhance the system stability.

One of the widely employed objective function for obtaining the control parameters of LFC is Time Integral of Absolute Error (ITAE) based on frequency deviation of both the interconnected areas defined as Δf1, Δf2, and deviation in tie line power ΔP12. The formulated objective function is expressed as

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

Many conventional control based approaches have been proposed in literature which are using linear and non-linear control scheme [17-21] for providing control in the load frequency control loop for controlling the frequency against the load changes. The next paradigm shift is in the use of Artificial intelligence based control for providing optimal control in the LFC loop [22-49]. Much of the work is associated with the implementation of expert control involving Fuzzy logic [22-26] and Artificial Neural Network based control [27-49].

LFC has made use of ANNs to improve performance and address a variety of issues ranging from controller designing and parametric tuning [27-32], handling the non-linear behavior of the power system by means of approximation and providing more accurate control which may sometime be self adjusting thus providing adaptive control [33-40], estimating the unkown dynamics [41-45], integration with other conventional controller like PID or replacing them completely [46-48].

The limitation in the reported work is little or no information about the selection of the ANN structure for implementing the intelligent controller. Neither any information about the formulation of the ANN network is provided. The current wok aims to systematically develop a framework for machine learning based LFC keeping in view of the available network type and learning algorithm for minimizing the frequency deviation at the earliest with least error.

II. BENCHMARK ANN MODEL

It's important to remember that while ANNs provide many benefits, there are some drawbacks as well. Choosing the right training data, designing the network architecture, and generalizing are essential components of employing ANNs for load frequency management efficiently. Furthermore, significant consideration must be given to safety and stability issues when applying neural network-based control in crucial infrastructure, such as power systems.

The numerous types of non-linear neural network architecture are inspired by the human brain. In essence, neural networks are taught using certain learning algorithms to estimate future predictions. The basic linear neuron architecture vectored input which forms the backbone or the building block of other types of ANN structure is shown in Fig. 2. It consist of two layers viz. input layer and the output layer. The input data set or pattern series is sent to the input layer in order to perform a specific task of classification, prediction or controlling. The input data is then processed through biases and weights at the hidden in accordance with the settled target and through the activation function the output is obtained. The generalized output achieved from thisnetwork with vectored input is represented as

$$F_t = f(Wn + b) \quad (3)$$

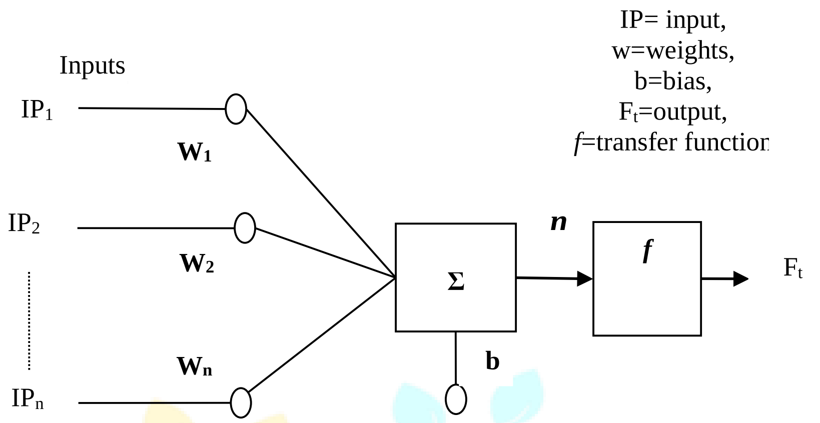

Figure 2: Simple network structure

A simplified benchmark three layer feedforward artificial neural network is shown in Fig. 3. The three layers are the input layer, hidden layer and the output layer. The input node receives the input data which is processed at the hidden layer through the weights and bias and then the output of the hidden layer is fed to the output layer, which consists of the total activation function response, weights, and biases in accordance with the targets [50].

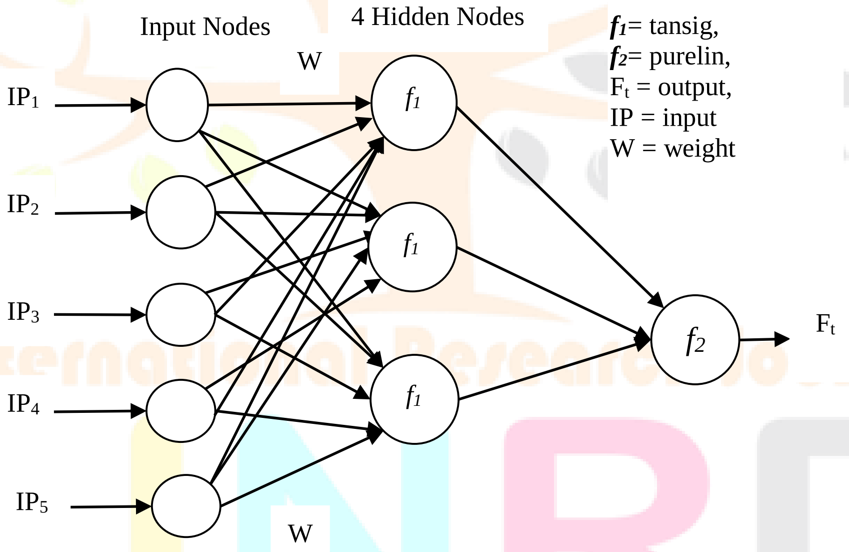

Figure 3: Simple feed forward neural network structure

The generalized output achieved from the the feed forward neural net irepresented as shown in Fig. 3 having 5 input nodes at the input layer, a hidden layer and a single output neuron. The depicted learning and and training takes place as per the following algorithm the hidden layer neuron output is given by (4) as assisted by vectored weight and bias, b

$$net_j = \sum_{i=0}^{n} w_{ih,} y_k + b_{kh} \qquad \text{for } i = 0,1,\ldots 5 \text{ and } h = 1,\ldots.,3) \quad (4)$$

$$z_k = f_h(net_l) \qquad \text{for } h = 1,2,3 \quad (5)$$

The netl is used to calculate the output of lth hidden node in which the wk,lis value of weight of the neuron connecting the input node ito the hidden layer node handyk is the kth input data.
The output of the hth hidden node is calculated as zl with activation function fhas (5). The activation function used at hidden layer is tangent sigmoid, tansigwhich is expressed as

$$f(IP) = \frac{2}{1 + e^{-2IP}} - 1 \quad (6)$$

The overall output is calculated as

$$F = f_0(\sum_{i=0}^{m} w_{l,m} y_l)(l = 1,2,\ldots,4) \quad (7)$$

where, the activation function fo of the ouptut layer and is generally the employed transfer function is pure linear (purelin) given by(8), the weight connected between hth hidden node and mth output node is wh,mfor this case m is 1

$$f(IP) = IP \quad (8)$$

The complexity of the system arises due to a large combination formed within the ANN structure selection owing to availability of a large number of network types, training techniques and activation function in ANN structure. A glimpse of the same is shown in Fig. 4 below.

Network Type

1. Cascade forward backpropagation network
2. Competitive network
3. Elman backpropagation network
4. Feedforward backpropagation network
5. Feedforward distributed time delay network
6. Feedforward time delay network
7. Generalized regression network
8. Hopfield network
9. Layer recurrent network
10. Linear layer design network
11. Linear layer train network
12. Learning vector quantization(LVQ) network
13. NARX network
14. NARX serial parallel network
15. Perceptron network
16. Probabilistic network
17. Radial Bias network
18. Self organizing map network

Heuristic Training Technique

1. traingd (gradient descent back propagation)
   a) traingd
   b) traingdm
   c) traingda
   d) trainrp

2. Numerical Optimization

Conjugate gradient training
   a) traincgf
   b) traincgp
   c) traincgb

Quasi Newton
   a) trainbfg
   b) trainoss
   c) trainlm

Levelberg-Marquardt
   a) trainlm
   b) trainbr

Transfer Function Type

1. Hardlim	2. Purelin	3. Logsig
4. Tansig	5. Satlin	6. Softmax
7. Compet	8. Poslin	9. Tribas
10. Radbas	11. Satlin	

Figure 4: ANN structure selection parameters [50]

All the network types are basically formed from the simple network structure shown in Fig. 2. For a perceptron layer the transfer function used is hardlim, for linear network the output transfer function is purelin. Both of these networks are single layer network.

The back propagation basedneuralnetwork has multiple layers thus corresponding to Fig. 3. Here the hidden layer can have tansig activation function and output layer will have purlin activation function

Another type of neural network is the recurrent type network which can be a two layer network. These network have feedback link going from the second layer to the first layer these network are useful for generating time varying parameters. The general type is shown below in Fig 5.Since these network features two feed forward and feedback pathways at the mid or hidden layer, hence the input is processed numerous times before it reaches the output, the delay or feedback serves as the memory. Compared to other networks, they have the benefit of being able to map more intricate and nonlinear time [50]

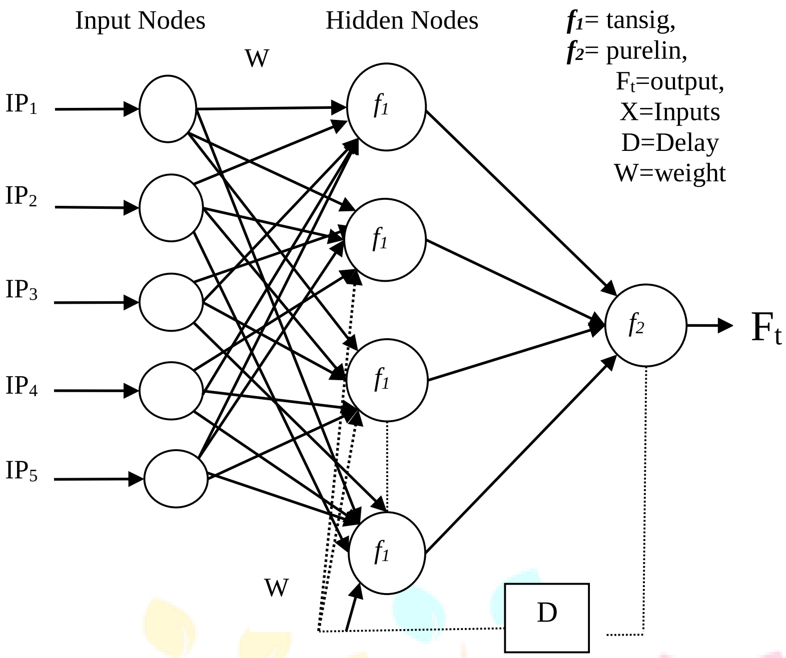

Figure 5: Three layer recurrent network

The next type of network are the control system based network which have three categories consisting of Model Reference controller , the NARMA controller and the NN predictive controller such controller helps in transforming the non-linear system dynamics to linear dynamics by the means of cancelling the non linearities

The probabilistic and the radial bias network makes use of the radbas transfer function and instead of summation as in simple neural network it makes use of the distribution function, the output layer still has the purelin transfer function. A generalized structure of the same is shown in Fig. 6.

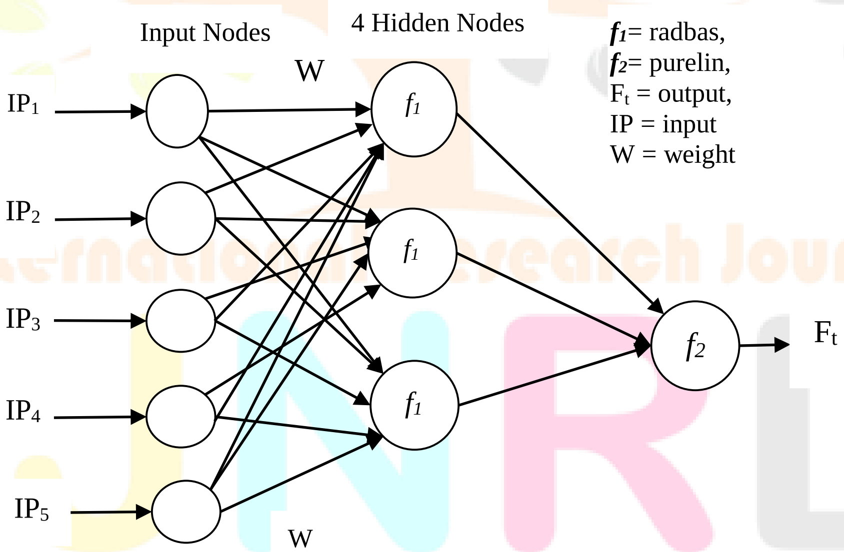

Figure 6: Three layer radial basis network

Similar to radial basis network is the generalized regression network and the probabilistic neural network has input, pattern, summation, and output layer network. The activation function is employed is purelin at the summation layer and radbasactivation function is used in the pattern layer [34]. Such a system is generally employed for time-series analysis.

III. METHODOLOGY

This section gives the insight of the methodology adopted for developing the framework for the machine learning based load frequency control. The first sub-section explains the adopted benchmark LFC model and the second subsection explains the ANN structure selection and modelling of the ANN based LFC controller.

3.1 Two area Benchmark LFC model

A generalized LFC model is shown in figure 7 below. This is a transfer function model and has been refereed from [15] and has been used as base model for all the two area networks. Each area have conventional power generation system consisting of a generator with time constant Tgi, a turbine with time constant Tti, a synchronous 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.

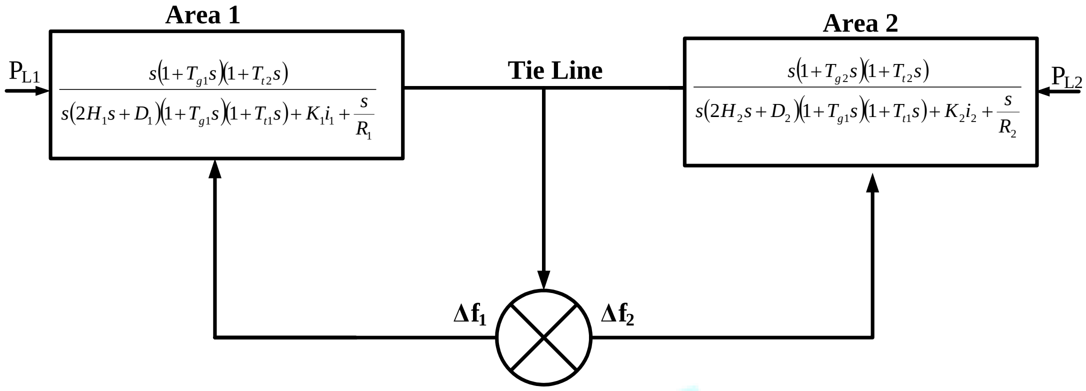

Figure 6: Benchmark two area LFC based network

The two areas are connected through the tie line and the error is fed to the PI controller which controls the governor turbine assembly which in turn controls the synchronous generator. The overall reacts to the load fluctuations which in turn create the imbalance which results in frequency deviation and to settle these frequency deviations the conventional PI controller reacts to the area control error thus allowing the transference of power through the tie line thus controlling the frequency. The selected parameter for the two areas, viz area 1 and area 2 are 0.2 s and 0.3 s as generator time constant, 0.5 s and 0.6 s as turbine time constant, 5 and 4 as inertia constant, 0.6 and 0.9 as frequency dependent load and with droop control of 0.05 and 0.625 for the respective areas.

3.2 ANN Model Selection

The balance between load and generation within the power grid is ensured by load frequency control (LFC), a crucial component of power system operation. While employing ANN for load frequency management the structure type, taining data and training algorithm have to be rightly selected for obtaining the best results.

Based upon the review of the available literature and the available network type the ANN network for performing LFC is broadly categorized as linear newtrok, Feedforward network and the recurrent network thus excluding he control network, radial basis network including the GRNN and probabilistic network.

The training algorithm are selected based upon the learning procedure adopted which is categorized as supervised and unsupervised learning [53]. Under the supervised learning the most effective ANN newrok structure are self organizing network including competitive network and LVQ network [50,53].

Based upon this information only supervised learning is available which include the heursitc techniques and numerical optimization technique. For the heuristic technique all the four techniques are opted due to inherent feature of using the learning with gradient decent. This forms the basic learning or training algorithm named taingd followed by batch training method which includes an acceleration factor and the algorithm is referred as traingdm. The next method employed is using gradient descent with variable learning rate, the training algorithm referred to as traingda and a resilient method denoted as tarinrp [50].
Though the above training method are good for linear network including with memory, multiple layer or with feedback but still for the recurrent neural network the numerical optimization techniques have also been employed. These are the famous and most employed trainlm famously known as Levenberg-Marquardt algorithm [37,41] and the other is traincgp involving conjugate gradient method [42]

Hence in this methodology, the three adopted model are Linear network, Feedforward Network and the Recurrent network. The learning model is whole set of heuristic model and two numerical optimization based learning methodology namely trainlm and traincgp.

IV. RESULTS AND DISCUSSION

The impact of using the different ANN model with different training algorithm when employed to the two area benchmark LFC model is discussed in this section. The conventional controller is replaced by the ANN based Machine learning algorithm and tested under the load perturbation of 0.1875 pu. A Comparison is drawn on the three selected ANN models viz. Linear network, Feedforward network and the recurrent network with the above mentioned six training algorithms to demonstrate the effectiveness of the adopted methodology.

Figure 7 shows the impact of Linear ANN network employing the heuristic training techniques and the numerical optimization training techniques. It is evident that traingd method gives the best result in the whole set of training algorithm where the frequency deviation settle to zero at a much faster speed followed by trainrp. In the numerical optimization training method both the algortihm gives nearly the same result but is less resilient to the heuristic method.

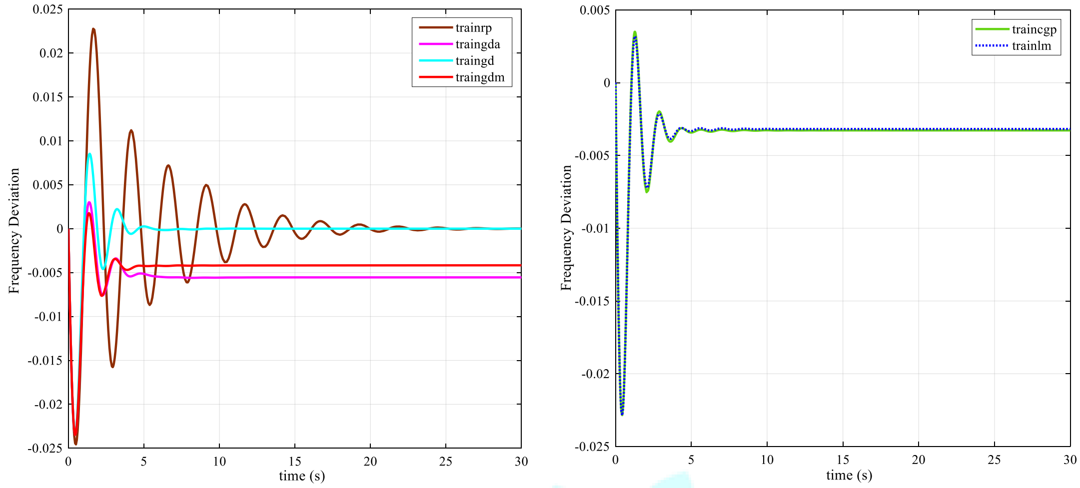

Figure 7: Frequency deviation in area 1 using Linear ANN network

Figure 8 shows the impact of Feedforward ANN network employing the heuristic training techniques and the numerical optimization training techniques. It is evident that traingdm method gives the best result in the whole set of training algorithm where the frequency deviation settle to zero at a much faster speed followed by traingda. In the numerical optimization training method both the algorithm gives nearly the same result but is less resilient to the heuristic method.

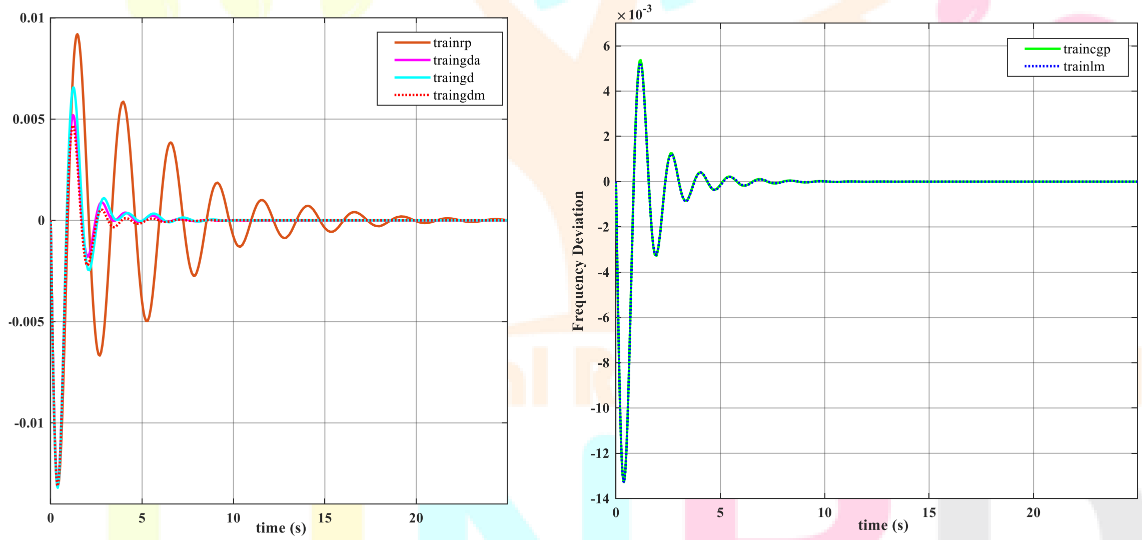

Figure 8: Frequency deviation in area 1 using Feedforward ANN network

Figure 9 shows the impact of Recurrent ANN network employing the heuristic training techniques and the numerical optimization training techniques. It is evident that traingda method gives the best result in the whole set of training algorithm where the frequency deviation settle to zero at a much faster speed followed by traingdm. In the numerical optimization training method trainlm performs better than traincgp but in comparison to heuristic methods numerical optimization training shows inferior control capabilities.

From the obtained results it is observed that recurrent networks provides the best control capability employing both the heuristic and numerical optimization training methodology in comparison to the linear and the Feedforward ANN network. In general traingd and traingda method are comparatively better training methods.

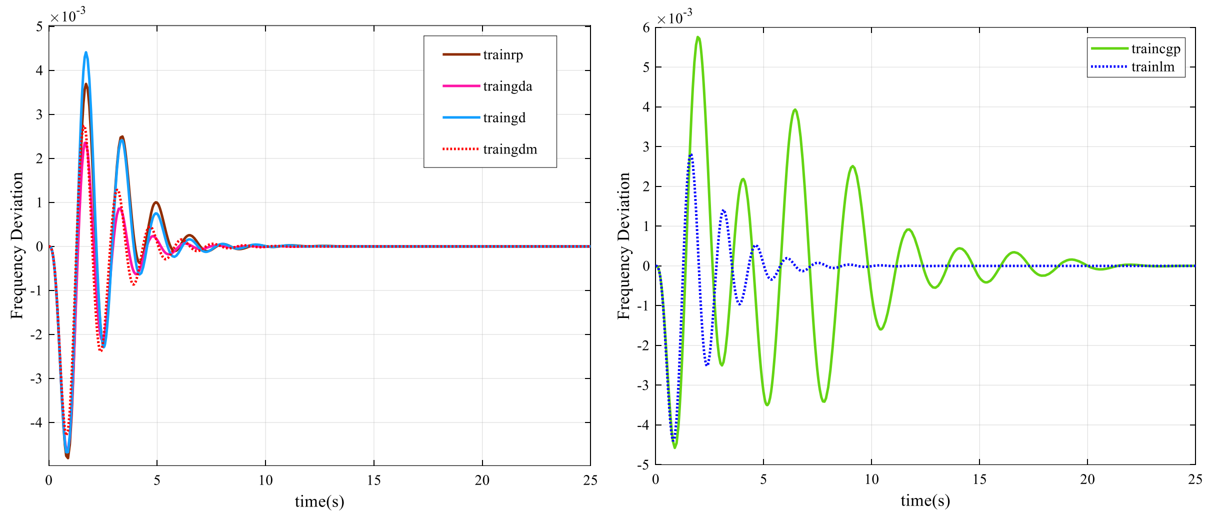

Figure 8: Frequency deviation in area 1 using Recurrent ANN network

V. CONCLUSION

For data classification and regression applications machine learning models are widely used. But proper methodology for selecting a machine learning based model and then deciding upon the structure, algorithm and performance analysis crieterion is generally left unanswered. For this, author's have proposed and demonstrated a methodology for the selection of machine learning model as applicable to famous load supply balance equation in power system. A comparison is drawn among the different available network architecture for settling the frequency deviation to zero at the earliest without offset in the two area load frequency control problem. The recurrent network provides the best result and for learning algorithms traingd and traingda method are comparatively better training methods.

REFERENCES

[1] G. Tsang, X. Xie and S. -M. Zhou. 2020. Harnessing the Power of Machine Learning in Dementia Informatics Research: Issues, Opportunities, and Challenges. IEEE Reviews in Biomedical Engineering, 13: 113-129.

[2] Z. A. Memon, R. Trinchero, P. Manfredi, F. Canavero, I. S. Stievano and Y. Xie, 2020. Machine Learning for the Uncertainty Quantification of Power Networks. IEEE Letters on Electromagnetic Compatibility Practice and Applications,2(4): 138-141.

[3] X. Shen, X. Zhang, Y. Huang, S. Chen and Y. Wang. 2020. Task Learning Over Multi-Day Recording via Internally Rewarded Reinforcement Learning Based Brain Machine Interfaces. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(12):3089-3099.

[4] Athar, S. Ali, M. M. Sheeraz, S. Bhattachariee and H. -C. Kim. 2021. Sentimental Analysis of Movie Reviews using Soft Voting Ensemble-based Machine Learning. Eighth International Conference on Social Network Analysis, Management and Security. Gandia, Spain

[5] R. Sharma and P. Kaushik. 2017. Literature survey of statistical, deep and reinforcement learning in natural language processing. International Conference on Computing, Communication and Automation. Greater Noida, India.

[6] Ganesh, A., Dahiya, R., & Singh, G. K. 2014. A Novel Robust STATCOM Control Scheme for Stability Enhancement in Multimachine Power System. Elektronika Ir Elektrotechnika, 20(4) : 22-28.

[7] G. Jia, H. -K. Lam, S. Ma, Z. Yang, Y. Xu and B. Xiao. 2020. Classification of Electromyographic Hand Gesture Signals Using Modified Fuzzy C-Means Clustering and Two-Step Machine Learning Approach. IEEE Transactions on Neural Systems and Rehabilitation Engineering,28(6) : 1428-1435.

[8] F. Jaffar, T. Farid, M. Sajid, Y. Ayaz and M. J. Khan. 2020. Prediction of Drag Force on Vehicles in a Platoon Configuration Using Machine Learning. IEEE Access, 8(1): 201823-201834.

[9] R. A. Welikala et al. 2020. Automated Detection and Classification of Oral Lesions Using Deep Learning for Early Detection of Oral Cancer. IEEE Access, 8(1): 132677-132693.

[10] R. Feng. 2021 A Bayesian Approach in Machine Learning for Lithofacies Classification and Its Uncertainty Analysis. IEEE Geoscience and Remote Sensing Letters, 18(1): 18-22.

[11] R. Mao et al. 2022. An Ultra-Energy-Efficient and High Accuracy ECG Classification Processor With SNN Inference Assisted by On-Chip ANN Learning. IEEE Transactions on Biomedical Circuits and Systems, 16(5) : 832-841.

[12] R. Elkadiri et al. 2014. A Remote Sensing-Based Approach for Debris-Flow Susceptibility Assessment Using Artificial Neural Networks and Logistic Regression Modeling. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7(12): 4818-4835.

[13] X. Chen, M. Yi and J. Huang. 2020. Application of a PCA-ANN Based Cost Prediction Model for General Aviation Aircraft. IEEE Access, 8(1): 130124-130135.

[14] M. V. Selvi and S. Mishra. 2020. Investigation of Performance of Electric Load Power Forecasting in Multiple Time Horizons With New Architecture Realized in Multivariate Linear Regression and Feed-Forward Neural Network Technique. IEEE Transactions on Industry Applications, 56 (5): 5603-5612.

[15] Hadi Saadat, Power System Analysis, McGraw-Hill Series in Electrical and Computer Engineering, New York.1999.

[16] Elgerd, O.I; Fosha, C.E. 1970. Optimum Megawatt-Frequency Control of Multiarea Electric Energy Systems" IEEE Trans. Power Apparatus, 89: 556 – 563.

[17] Neelamsetti, Kiran & Indragandhi, V. 2018. Analysis on various optimization techniques used for Load Frequency Control in power system. 15.

[18] P. Ojaghi and M. Rahmani. 2017. LMI-Based Robust Predictive Load Frequency Control for Power Systems With Communication Delay. IEEE Transactions on Power Systems, 32(5): 4091-4100.

[19] Gholamrezaie, M. G. Dozein, H. Monsef and B. Wu. 2018. An Optimal Frequency Control Method Through a Dynamic Load Frequency Control (LFC) Model Incorporating Wind Farm. IEEE Systems Journal, 12(1): 392-401.

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

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

[22] H. Bevrani and P. R. Daneshmand. 2012. Fuzzy Logic-Based Load-Frequency Control Concerning High Penetration of Wind Turbines. IEEE Systems Journal, 6(1): 173-180.

[23] 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, : 1822-1830, 2014.

[24] T. Fernando, K. Emami, S. Yu, H. H. Iu and K. P. Wong. 2016. A Novel Quasi-Decentralized Functional Observer Approach to LFC of Interconnected Power Systems. IEEE Transactions on Power Systems, 31(4): 3139-3151.

[25] Z. Cheng, D. Yue, S. Hu, X. Xie and C. Huang.Detection-based weighted H∞ LFC for multi-area power systems under DoS attacks. in IET Control Theory & Applications, vol. 13, no. 12, : 1909-1919, 2019.

[26] S. Aziz, H. Wang, Y. Liu, J. Peng and H. Jiang. 2019. Variable Universe Fuzzy Logic-Based Hybrid LFC Control With Real-Time Implementation. IEEE Access, 7: 25535-25546.

[27] S. Sundaram and T. Jayabarathi. 2011. Load Frequency Control using PID tuned ANN controller in power system. 1st International Conference on Electrical Energy Systems, 269-274.

[28] Demiroren, H. L. Zeynelgil and N. S. Sengor. 2001. The application of ANN technique to load-frequency control for three-area power system. IEEE Porto Power Tech Proceedings, 5(2).

[29] Al-Majidi SD, Kh. AL-Nussairi M, Mohammed AJ, Dakhil AM, Abbod MF, Al-Raweshidy HS. 2022. Design of a Load Frequency Controller Based on an Optimal Neural Network. Energies, 15(17).

[30] Mohamed I. Mosaad, Fawzan Salem. 2014. LFC based adaptive PID controller using ANN and ANFIS techniques. Journal of Electrical Systems and Information Technology, 1(3): 212-222.

[31] N. E. Y. Kouba, M. Menaa, M. Hasni and M. Boudour. 2016. LFC enhancement concerning large wind power integration using new optimised PID controller and RFBs. IET Generation, Transmission & Distribution, 10(16): 4065-4077.

[32] Osinski, G. Villar Leandro and G. H. da Costa Oliveira. 2019. Fuzzy PID Controller Design for LFC in Electric Power Systems. IEEE Latin America Transactions, 17(1): 147-154.

[33] H. Haes Alhelou, M. E. H. Golshan and N. D. Hatziargyriou. 2019. A Decentralized Functional Observer Based Optimal LFC Considering Unknown Inputs, Uncertainties, and Cyber-Attacks. IEEE Transactions on Power Systems, 34(6): 4408-4417.

[34] Yang et al. 2019. Inertia-adaptive model predictive control-based load frequency control for interconnected power systems with wind power. IET Generation, Transmission & Distribution, 14(22): 5029-5036.

[35] Zhou, Z. Quan and Y. Li. 2020. Hybrid Model Predictive Control of ANPC Converters With Decoupled Low-Frequency and High-Frequency Cells. IEEE Transactions on Power Electronics, 35(8): 8569-8580.

[36] Singh Jaswinder, Aman Ganesh. 2008. Design and Analysis of GA based Neural/Fuzzy Optimum Adaptive Control. WSEAS Transactions on Systems and Control, 3(5) : 375-382.

[37] Z. Yan and Y. Xu. 2019. Data-Driven Load Frequency Control for Stochastic Power Systems: A Deep Reinforcement Learning Method With Continuous Action Search. IEEE Transactions on Power Systems, 34(2): 1653-1656.

[38] J. Yang, X. Sun, K. Liao, Z. He and L. Cai. 2019. Model predictive control-based load frequency control for power systems with wind-turbine generators. IET Renewable Power Generation, 13(15): 2871-2879.

[39] Jiawen Li, Tao Yu, Haoyang Cui. 2022. A multi-agent deep reinforcement learning-based "Octopus" cooperative load frequency control for an interconnected grid with various renewable units. Sustainable Energy Technologies and Assessments, 51(2) : pp. 10189-10198.

[40] Qi.X., Zheng J. and Mei Fei. 2022. Model Predictive Control-based load frequency regulation of Grid-Forming Inveter based power Systems. Front. Energy Resources, 10.

[41] Qian and G. Fan. 2018. Neural-Network-Based Terminal Sliding Mode Control for Frequency Stabilization of Renewable Power Systems. IEEE/CAA Journal of Automatica Sinica, 5(3) : 706-717.

[42] H. Haes Alhelou, M. E. H. Golshan and N. D. Hatziargyriou. 2019. A Decentralized Functional Observer Based Optimal LFC Considering Unknown Inputs, Uncertainties, and Cyber-Attacks. IEEE Transactions on Power Systems, 34(6): 4408-4417.

[43] J. Ramlal, A. Singh, S. Rocke and M. Sutherland. 2019. Decentralized Fuzzy H∞ Iterative Learning LFC With Time-Varying Communication Delays and Parametric Uncertainties. IEEE Transactions on Power Systems, 34(6): 4718-4727.

[44] X. Lv, Y. Sun, S. Cao and V. 2020. Dinavahi.Event-triggered load frequency control for multi-area power systems based on Markov model: a global sliding mode control approach. IET Generation, Transmission & Distribution, 14(21): 4878-4887.

[45] H. Haes Alhelou, M. E. Hamedani Golshan and N. D. Hatziargyriou. 2020. Deterministic Dynamic State Estimation-Based Optimal LFC for Interconnected Power Systems Using Unknown Input Observer. IEEE Transactions on Smart Grid, 11(2): 1582-1592.

[46] Nasiruddin, G. Sharma, K. R. Niazi and R. C. Bansal. 2017. Non-linear recurrent ANN-based LFC design considering the new structures of Q matrix. IET Generation, Transmission & Distribution, 11(11): 2862-2870.

[47] Erratum. 2018. Non-linear recurrent ANN-based LFC design considering the new structures of Qmatrix. in IET Generation, Transmission & Distribution, 12(16): 3912-3912.

[48] X. Wang, Q. Zhao, B. He, Y. Wang, J. Yang and X. Pan. 2017. Load frequency control in multiple microgrids based on model predictive control with communication delay. The Journal of Engineering, 13: 1851-1856.

[49] Beaufays F., Abdel-Magid, Y., Widrow B. 1994. Application of neural networks to load-frequency control in power system. Neural Networks, 7(1): 183 -194.

[50] www.mathworks.com

[51] Ganesh Aman, Dahiya R. and Singh G.K. 2014.A novel STATCOM wide area feedback controller for improving stability in multimachine system. International Conference on Power Systems, Energy, Environment : 204 – 210.

[52] Gireesh Kumar Devineni, Aman Ganesh, 2020. Problem Formulations, Solving Strategies, Implementation Methods & Applications of Selective Harmonic Elimination for Multilevel Converters. Journal Européen des Systèmes Automatisés, 53(6) : 939-952.

[53] S. Rajesekran and G.A. Vijyalaxshmi Pai. 2007. Neural Netwroks, Fuzzy Logic and Genetic Algorithms: Synthesis and Application. PHI.

[54] Lera and M. Pinzolas. 2002. Neighborhood based Levenberg-Marquardt algorithm for neural network training. IEEE Transactions on Neural Networks, 13(5) : 1200-1203.

[55] Y. H. Dai and Y. Yuan. 1999. Convergence Properties of Beale-Powell Restart Algorithm. Science in China Series A Mathematics.