A Hopfield Neural Networks in Identification of Redistribution Energy based Load Balancing

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***Abstract---*These works involve the purpose of multilayer Hop field neural network and dynamic neural network for the load frequency control of two-area power systems. Energy efficient wireless networks are the primary research study objective for billions of device applications like IoT (Internet of Things), smart grids and CPS. Monitoring of multiple physical events using sensors and data collection at central gateways is the all-purpose architecture follow by most commercial, residential and test bed implementations. The majority of the proceedings monitored at usual intervals are mainly redundant/minor variations leading to large wastage of data storage resources in big data servers and communication energy at relay and sensor nodes. In this project a novel architecture of Hop field Neural Network (NN) based day ahead steady state forecasting engine is implementing at the gateway using historical database. Gateway generate an optimal transmit schedules based on NN outputs thereby reducing the redundant sensor data when there is minor variations in the respective predicted sensor estimates. It is observed that NN based load forecasting for power monitoring system predicts load with less than 3% Mean Absolute Percentage Error (MAPE). Gateway forward transmit schedules to all power sensing nodes day ahead to reduce sensor and relay nodes communication energy. Matlab based simulation for evaluating the benefits of proposed model for extending the wireless network life time is developed and confirmed with an emulation scenario of our testbed. Network life time is improved by 43% from the observed results using proposed model.This paper is mainly concerned with an investigation of the suitability of Hopfield neural network structures in solving the power economic dispatch problem.**

Keywords:Frequency Control, Transient Analysis, Load Flow, Hopfield Model, Recall and Recognition

I. Introduction

In electric power generation, system disturbances caused by load fluctuations result in changes to the desired frequency value. Load Frequency Control (LFC) is a very important issue in power system operation and control for supplying sufficient and both good quality and reliable power. Neural networks have been applied to a wide variety of problem domains to learn models that are able to perform such interesting tasks as steering a motor vehicle recognizing genes in uncharacterized DNA sequences scheduling payloads for the space shuttle and predicting exchange rates Although neural network learning algorithms have been successfully applied to a wide range of supervised andunsupervised learning problems they have not often been applied in data mining settings in which two fundamental considerations are the comprehensibility of learned models and the time required to induce models from large data sets [2]. The main objective of Load Frequency Control (LFC) is to regulate the power output of the electric generator within an area in response to changes in system frequency and tie-line loading. Thus the LFC helps in maintaining the scheduled system frequency and tie-line power interchange with the other areas within the prescribed limits. Most LFCs are primarily composed of an integral controller [4]. The integrator gain is set to a level that the compromises between fast transient recovery and low overshoot in the dynamic response of the overall system. This type of controller is slow and does not allow the controller designer to take in to account possible changes in operating condition and non-linearities in the generator unit. Moreover, it lacks in robustness. Therefore the simple neural networks can alleviate this difficulty. The ANN is applied to self tune the parameters of PID controller. Multi area system, have been considered for simulation of the proposed self tuning ANN based PID controller [7]. The electricity industry is turning increasingly to renewable sources of energy to generate electricity. Wind energy has been the fastest growing and most widely utilized of the emerging renewable energy technology in electricity systems within the last several years and all factors indicate that the growth will continue for many years in the future.

In this paper, a method is proposed using a new mapping technique, which has been described in [8,10], for Hopfield neural networks to solve the quadratic programming problems, subject to a number of inequality and equality constraints, which can be handled by adding corresponding terms to the energy function.

Neural network techniques are considered to build non-linear ANN controller with high degree of performance [9]. In this simulation study, Single area, two area and three area power systems are chosen and load frequency control of this system is compared for conventional PI controller and ANN controller.

Following are some important points to keep in mind about discrete Hopfield network −

- This model consists of neurons with one inverting and one non-inverting output.
- The output of each neuron should be the input of other neurons but not the input of self.
- Weight/connection strength is represented by I_n.

Connections can be excitatory as well as inhibitory. It would be excitatory, if the output of the neuron is same as the input, otherwise inhibitory.Weights should be symmetrical.

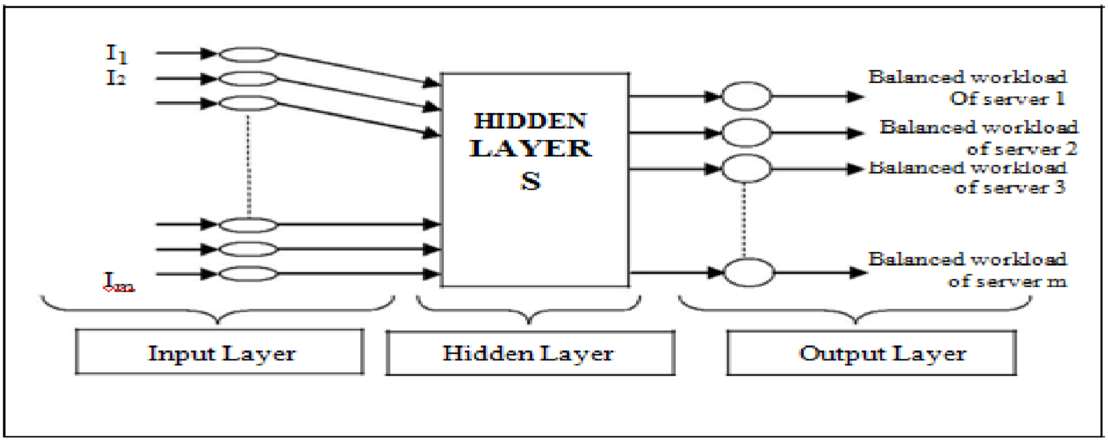

Fig. 1. Load Frequency Analysis

A Hopfield network is a neural network with a graph G = (U, C) that satisfies the following conditions:

(i) Uhidden = ∅, Uin = Uout = U,
(ii) C = U × U − {(u, u) | u ∈ U}.

Load-frequency control (LFC) plays an essential role to allow power exchanges and to supply better conditions for the electricity trading [5]. Also, time delays in such systems can reduce system performance and even cause system instability on frequency or other parameters. Gain scheduling is a controller design technique used for non-linear systems. Future loads can be extrapolated using the time series model assuming a stationary load series.

I. PROBLEM DEFINITION

In order to keep the power system in normal operating state, a number of controllers are used in practice. As the demand deviates from its normal operating value the system state changes. Different types of controllers based on classical linear control theory have been developed in the past [11]. Because of the inherent non-linearities in system components and synchronous machines, neural network techniques are considered to build non-linear ANN controller with high degree of performance. Most load frequency controllers are primarily composed of an integral controller. The integrator gain is set to a level that compromise between fast transient recovery and low overshoot in the dynamic response of the overall system. This type of controller is slow and does not allow the controller designer to take into account possible non-linearities in the generator unit.

In this paper, we will investigate both BP and Hopfield neural networks as the solvers for linear equations (1). The remainder of this paper is organized in following sections.

A. Dynamic Neural Network

Dynamic neural units (DNUs), as the basic elements of dynamic neural networks, receive not only external inputs but also state feedback signals from themselves and other neurons. The synaptic connections in a DNU contain a self-recurrent connection that represents a weighted feedback signal of its state and lateral inhibition connections, which are the state feedback signals from other DNUs in the network. in terms of information processing, the feedback signals involved in a DNU deal with some processing of the past knowledge and store internal potential or internal state that is used to describe the dynamic characteristics of the network.

B. Load Frequency Control

A dynamic neural network model has unconstrained connectivity and has dynamical elements in its neuro processing units. In general, there are l input signals which can be time-varying, n dynamic neuron units, n bias terms, and m output signals. The units have dynamics associated with them, and they receive input from themselves, bias term and from all other units. The output of a unit is a general sigmoid function of a state variable xi associated with the unit. The output of the overall network is a linear weighted sum of the unit outputs. The bias term bi is added to the unit inputs.

C.The Hopfield Model

The Hopfield model's dynamics are composed of a non-linear, iterative, asynchronous transformation of the network state [Hop82]. The process may include a stochastic noise which is analogous to the 'temperature'; T in statistical mechanics. Formally, the Hopfield model is described as follows: Let neuron's i state be a binary variable Si, taking the values ± 1 denoting a firing or a resting state, correspondingly.

D. Recall and Recognition

Recall is considered successful when upon starting from an initial cue the network converges to a stable state which corresponds to the learned memory nearest to the input pattern. Inter-pattern distance is measured by the Hamming distance between the input and the learned item encodings. If the network converges to a non-memory stable state, its output will stand failure of recall; response.

E. Design of ANN Controller

The range over which error signal is in transient state, is observed. Responding values of the proportional, integral and derivative constants are set. This set is kept as target. Range of error signal is taken as the input. This input – target pair is fed and new neural network is formed using “nntool” in the MATLAB Simulink software.Demonstration of Hopfield networks as associative memory:

- Visualization of the association/recognition process
- Two-dimensional networks of arbitrary size

	1	2	3	4	5	6	7
1	NaN	45	120	NaN	45	NaN	Na
2	NaN	NaN	120	NaN	NaN	NaN	Na
3	NaN	60	120	NaN	60	NaN	Na
4	NaN	NaN	120	NaN	NaN	NaN	Na
5	NaN	NaN	120	NaN	NaN	NaN	Na
6	NaN	NaN	120	NaN	NaN	NaN	Na
7	15	120	120	NaN	120	NaN	Na
8	30	30	120	NaN	30	NaN	Na

Fig 2: Input Datasets

The goal of the Hopfield network is to be able to correctly recall one of NumPatt “memory” patterns Mem(a) , a=1,2,...NumPatt, when presented with a stimulus pattern that is closeto one of the memory patterns constructed by 15000 datasets approximately. The memory patterns each consist of N elements whose values are either +1 or -1. For example, if the memory patterns were faces drawn in black-andwhite, then N might represent the number of pixels in the drawing of the face, a pixel value of +1 might represent a white pixel, and a pixel value of -1 might represent a black pixel.

For networks with a symmetric connection matrix it is possible to define an energy function or Lyapunov function, a finite-valued function of the state that always decreases as the states change.

Use Energy Minimization to solve Optimization problems General procedure:

• Transform function to optimize into a function to minimize.

• Transform function into the form of an energy function of a Hopfield network.

• Read the weights and threshold values from the energy function.

• Construct the corresponding Hopfield network.

• Initialize Hopfield network randomly and update until convergence.

• Read solution from the stable state reached.

• Repeat several times and use best solution found.

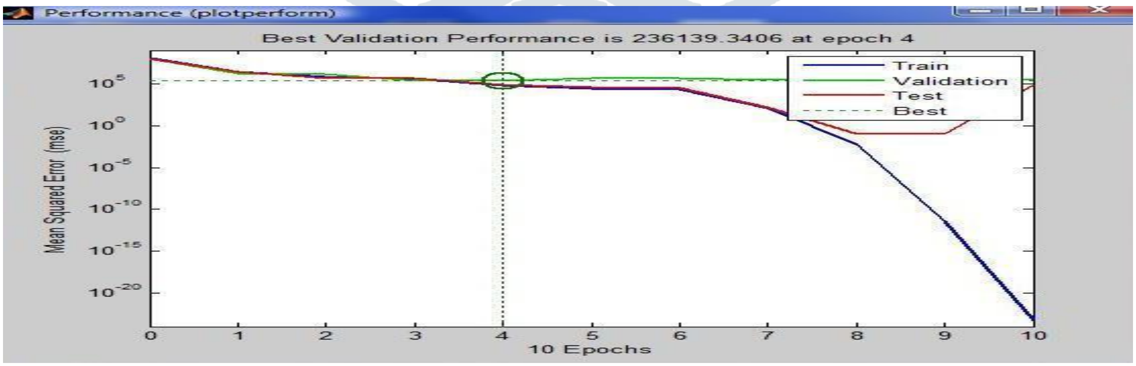

Fig 3: ANN performance in training, test and validation stages

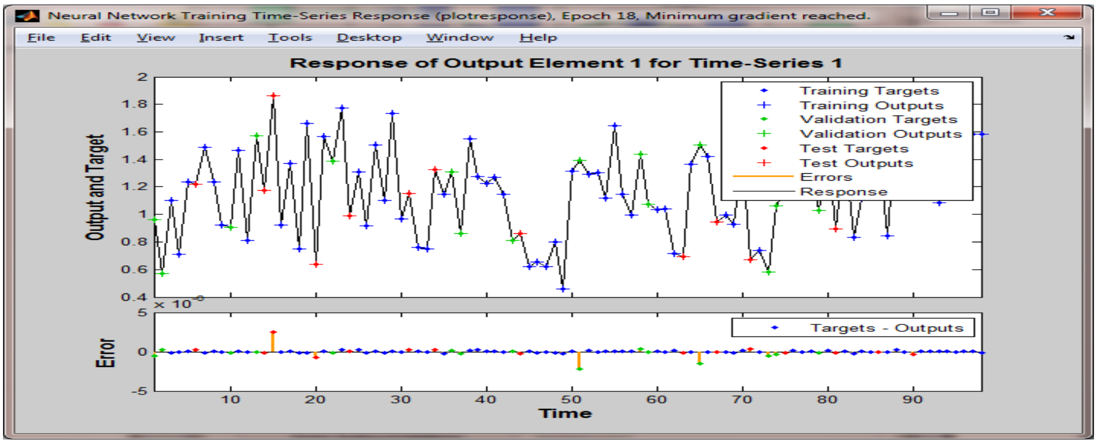

Fig 4: Response of Output Element

Weights and Biases obtained are fed to back propagation algorithm using approx. steepest descent method. Thus the neural network is well trained. Updated weights and biases are given to a fresh neural network. Now the neural network is ready for operation.

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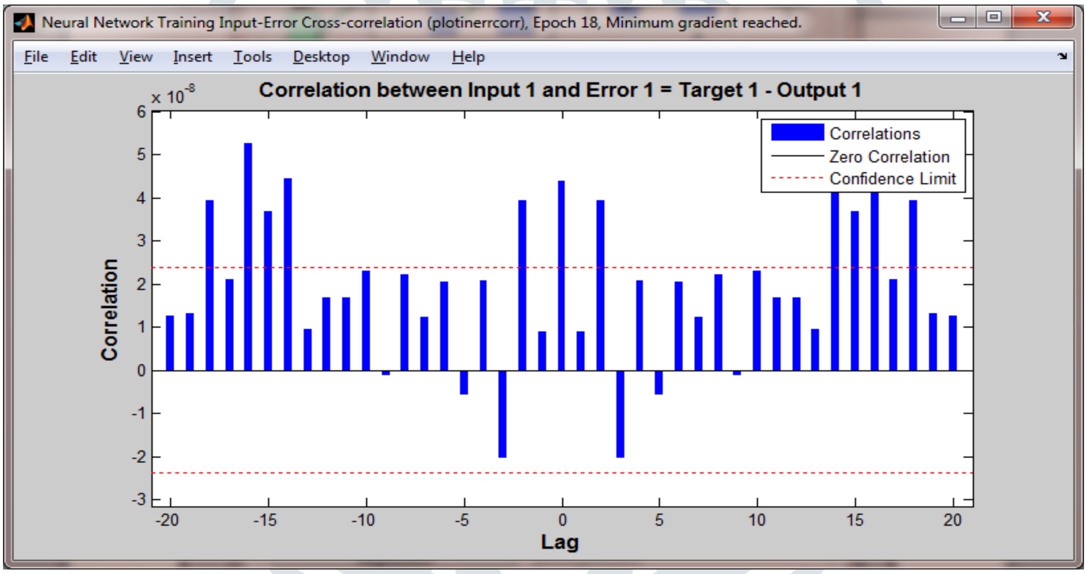

Fig 5: Correlation of Input Output

This input- target pair is fed and new network is formed using “nntool” in the MATLAB Simulink software. Weights and biases obtained are fed to back propagation algorithm using approximation. Steepest descent method. Thus the neural network is well trained. Updated weights and biases are given to a fresh neural network. Now the neural network is ready for operation. The error signal is given as input to the neural network. Desired target for each input value is obtained. The above neural network is written as program and is incorporated in the MATLAB function tool, in Simulink diagram.

III.RESULT AND DISCUSSION

The MATLAB Neural Network Toolbox was used for generating network architecture. In this study, normalized secondary currents of transformer were taken as input of the Hopfield Neural Network. The output of the Hopfield Neural Networkis the normalized values of Total Harmonic Distortions of current. There is no particular formula to choose suitable network architecture for an application. The suitable network size is found by trial and error. By trial and error, it was found that the suitable network size for this system with 1 input and 1 output was a network with two hidden layers in this work, sigmoid activation functions are used for both the hidden layers and output layer. The feed-forward back propagation technique is used for training ANN.

IV. CONCLUSION

From the simulation results obtained for load disturbances for ANN controller, PID (Proportional Integral Derivative) controller, Conventional integral controller can conclude that ANN controller is faster than the other, Peak undershoot is reduced, Settling time is reduced. The superiority of ANN controller is established in the cases of two area systems. From the Qualitative and Quantitative comparison of the results we can conclude that the ANN controller yields better results. ANN controller gives minimum IAE (International Aero Engines)/ISE (Identity Services Engine) /ITAE (Integral of Time Multiply Absolute Error) compared to the conventional integral and PID controllers. The simulation studies were also done for change in the operating conditions like change in governor time and turbine time constants.

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