GLOBAL JOURNAL OF ENGINEERING, DESIGN & TECHNOLOGY
(Published By: Global Institute for Research & Education)
www.gifre.org

Design of Intelligent Controller for Load Frequency Control of Multi Area Hydrothermal System

C.Srinivasa Rao
Dept. of EEE, G.Pullaiah College of Engineering and Technology, Kurnool, India

Abstract

This paper presents the design of controller based on the principles of Neural networks. The concept of artificial intelligent techniques greatly helps in overcoming the disadvantages posed by the conventional controllers. A hierarchical architecture of three layer feed forward neural network (NN) is proposed for controller design based on back propagation algorithm (BPA). Area Control Error (ACE) is considered as input to the neural network controller and the output of the controller is provided to the governor in each area. The proposed controllers are tested for a two area hydrothermal system. Simulation results show that the limitations of conventional controller can be overcome by including Neural concept and thereby the dynamic response of the system with respect to peak time, overshoot and settling time can be improved drastically.

Keywords: Automatic Generation Control, Hydrothermal system, Neural network, Back propagation algorithm, Area control error.

I. Introduction

Large scale power systems are normally composed of control areas or regions representing coherent groups of generators. In a practically interconnected power system, the generation normally comprises of a mix of thermal, hydro, nuclear and gas power generation. However, owing to their high efficiency, nuclear plants are usually kept at base load close to their maximum output with no participation in the system Automatic generation control (ACE). Gas power generation is ideal for meeting the varying load demand. Gas plants are used to meet peak demands only. Thus the natural choice for AGC falls on either thermal or hydro units. Literature survey shows that most of earlier works in the area of AGC pertain to interconnected thermal systems and relatively lesser attention has been devoted to the AGC of interconnected hydro-thermal system involving thermal and hydro subsystem of widely different characteristics. Concordia and Kirchmayer [1] have studied the AGC of a hydro-thermal system considering non-reheat type thermal system neglecting generation rate constraints. Kothari, Kaul, Nanda [2] have investigated the AGC problem of a hydro-thermal system provided with integral type supplementary controllers. The model uses continuous mode strategy, where both system and controllers are assumed to work in the continuous mode. Perhaps Nanda, Kothari and Satsangi [3] are the first to present comprehensive analysis of AGC of an interconnected hydrothermal system in continuous-discrete mode with classical controllers. It is known that load-frequency control systems include an integral controller as secondary controller in conventional control configurations. The integrator gain is set to a level that compromise between fast transient recovery and low overshoot in dynamic response of the system. Unfortunately, this type of controller is considerably slow. Because of this, the recovery of transients in the power system against to the load perturbations spends very long time.

In recent years intelligent methods such as Fuzzy logic (FL) have been applied to the load frequency control problem [4-7]. The salient feature of these soft computing techniques are that they provide a model-free description of control systems and do not require any model identification. But the main drawbacks of ANN include large number of neurons in the hidden layers for complex function approximation, and very large training time is required. Since artificial neural network configuration will be used to control the system, back propagation algorithm is used as a learning rule to cope with the continuous time dynamics.

In this study, a step load change in each area is considered. For comparison, the considered power system is controlled by using both conventional integral controller and neural network controller for the case mentioned above. The results obtained show that the ANN configuration using back propagation algorithm applied for AGC of power system gives good dynamic response with respect to conventional controller.

II. Dynamic Mathematical Model

Electric power systems are complex, nonlinear dynamic system. The load frequency controller controls the control valves associated with High Pressure (HP) turbine at very small load variations [8]. The system under investigation has tandem-compound single reheat type thermal system. Each element (Governor, turbine and power system) of the system is represented by first order transfer function at small load variations in according to the IEEE committee report [8]. Two system nonlinearities likely Governor Deadband and Generation Rate Constraint (GRC) are considered here for getting the realistic response. Governor Deadband is defined as the total magnitude of the sustained speed change within which there is no change in the valve position [8]. It is required to avoid excessive operation of the governor. GRC is considered in real power systems because there exits a maximum limit on the rate of change in the generating power. Figure 1 shows the transfer function block diagram of a two area interconnected network .The parameters of two area model are defined in Appendix.

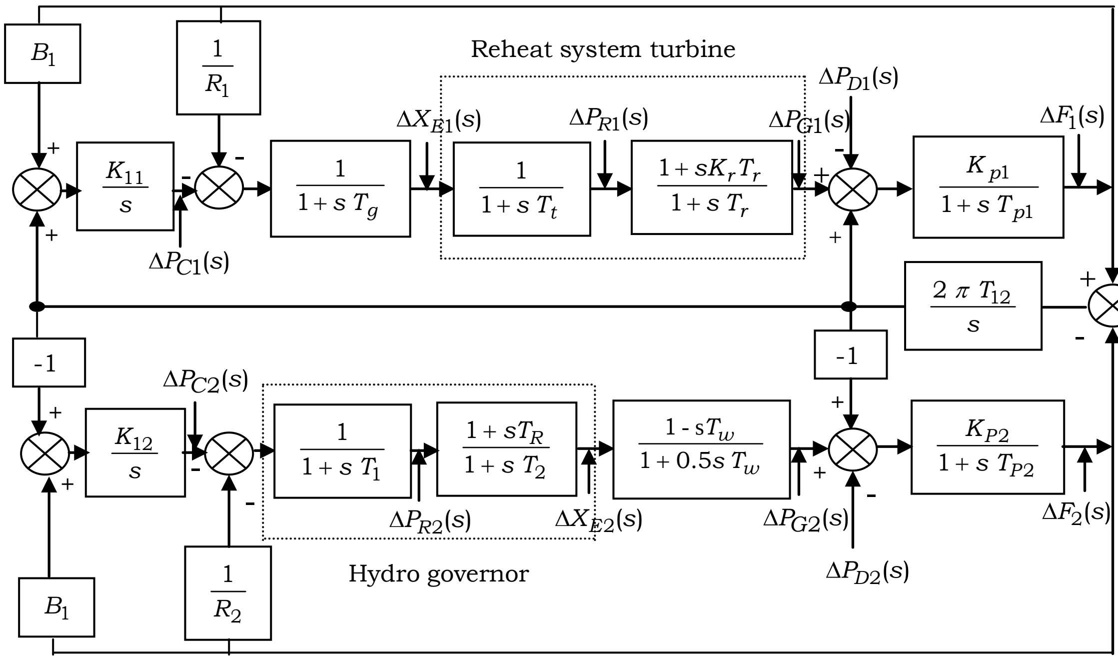

Fig. 1 Two Area Interconnected Thermal-Gas system

III. Back Propagation Algorithm

In the field of electrical engineering, one of the most exciting and potentially profitable recent developments is the increasing use of artificial intelligence techniques like neural networks in the design of various controllers. Artificial neural networks have been applied to many problems, and have demonstrated their superiority over classical methods when dealing with noisy or incomplete data. Neural networks are well suited to this method, as they have the ability to pre-process input patterns to produce simpler patterns with fewer components. A fascinating feature of the brain is that its physical organization reflects the organization of the external stimuli that are presented to it. In view of this back propagation algorithm has been used to design controller. In this back propagation algorithm the weights from input layer-hidden layer-output layer are updated iteratively during the learning phase. The updation of weights in back-propagation algorithm is done as follows:

The error signal at the output of neuron j at iteration n is given by

$$e_j(n) = d_j(n) - y_j(n) \tag{1}$$

The instantaneous value of error for neuron j is $\frac{1}{2}e_j^2(n)$. This instantaneous value $\varepsilon(n)$ of total error is obtained by summing $\frac{1}{2}e_j^2(n)$ of all neurons in output layer

$$\varepsilon(n) = \frac{1}{2}\sum_{j\in c} e_j^2(n) \tag{2}$$

where c includes all neurons in the output layer. Average squared error is given by

$$\varepsilon_{avg} = \frac{1}{N}\sum_{n=1}^{N}\varepsilon(n) \tag{3}$$

where N is total number of patterns in training set. So minimization of ε_{avg} is required. So back propagation algorithm is used to update the weights. Induced local field $v_j(n)$ produced at input of activation function is given by

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n) X_i(n) \tag{4}$$

where m is the number of inputs applied to neuron j. So the output can be written as

$$y_j(n) = \phi_j(v_j(n)) \tag{5}$$

The back propagation algorithm applies a correction $\Delta w_{ji}(n)$ to synaptic weights $w_{ji}(n)$ which is proportional to partial derivative $\frac{\partial\varepsilon(n)}{\partial w_{ji}(n)}$, which can be written as

$$\frac{\partial\varepsilon(n)}{\partial w_{ji}(n)} = \frac{\partial\varepsilon(n)}{\partial e_j(n)}\cdot\frac{\partial e_j(n)}{\partial y_j(n)}\cdot\frac{\partial y_j(n)}{\partial v_j(n)}\cdot\frac{\partial v_j(n)}{\partial w_{ji}(n)} \tag{6}$$

Differentiating the equation (2) with respect to $e_j(n)$

$$\frac{\partial \varepsilon(n)}{\partial e_j(n)} = e_j(n) \tag{7}$$

Differentiating equation (1) with respect to $y_j(n)$

$$\frac{\partial e_j(n)}{\partial y_j(n)} = -1 \tag{8}$$

Differentiating equation (5) we get

$$\frac{\partial y_j(n)}{\partial v_j(n)} = \phi_j'(v_j(n)) \tag{9}$$

Differentiating equation (4) with respect to $w_{ji}(n)$

$$\frac{\partial v_j(n)}{\partial w_{ji}(n)} = X_i(n) \tag{10}$$

So using equations (7-10) in equation (6) we get

$$\frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} = -e_j(n)\phi_j'(v_j(n))X_i(n) \tag{11}$$

The correction $\Delta w_{ji}(n)$ applied to $w_{ji}(n)$ is defined by

$$\Delta w_{ji}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} \tag{12}$$

where η is learning rate parameter. Figure 2 shows the architecture of neural network considered for this work. It can be seen that the Area Control Error (ACE) and rate of change of ACE are considered as inputs in the input layer and ΔP_c is considered as output in the output layer. Figure 3 shows the MATLAB/SIMULINK block implementation of the above logic. It can be seen from the figure that input is to be taken as ACE of the two area system

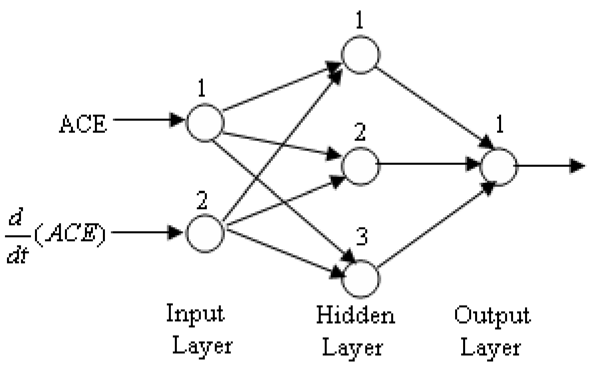

Figure. 2. Architecture of Neural Network Considered

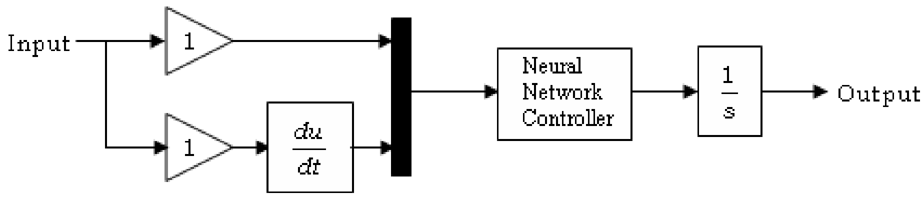

Figure. 3. MATLAB/SIMULINK Implementation of logic

IV. Result and Discussion

The proposed system in modeled in MATLAB/SIMULINK environment and the results have been presented. A load change of 0.04 p.u M.W in each area has been considered to study the comparison between neural network controller and integral controller. A value of 0.5 has been considered as the gain of integral controller. The training of the network has been done in neural network toolbox under MATLAB environment. The development environment for neural network toolbox is shown in Figure 4. As seen from figure 4, the network is trained with the 'train' inputs which contain the ACE and rate of change of ACE values obtained through traditional integral controller. As the back-propagation model refers to supervised learning, the target outputs during training phase are also provided in 'train_target'. The test patterns are also provided to the network in the form of 'test' input. The network with 2 input nodes-3 hidden nodes-1 output node will look like as shown in Figure 5.

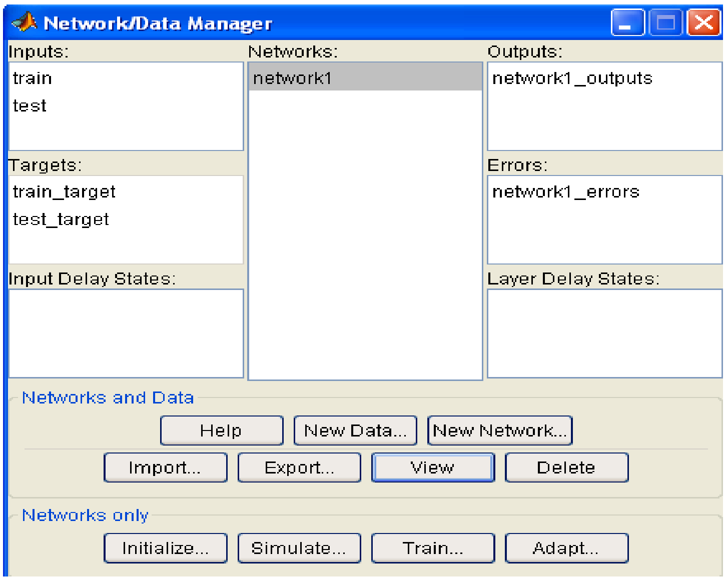

Figure. 4. Development environment for neural network toolbox

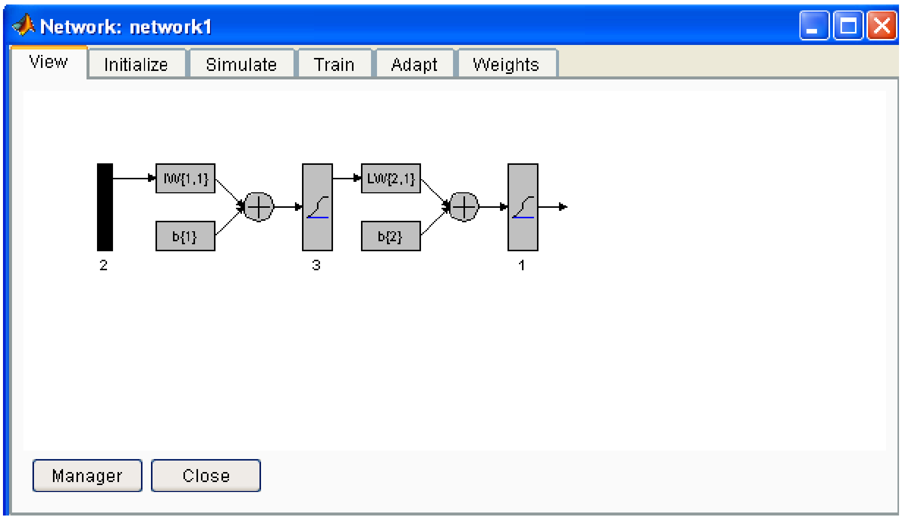

Figure. 5. Structure of the network

The activation function used in this work for both the layers is log-sig function. The adaptation learning function used in this work is LEARNGDM. Table 1 shows the values of weights between input layer and hidden layer obtained during training phase, where the rows correspond to input nodes and columns correspond to hidden nodes. Table 2 shows the bias value at the hidden nodes. Table 3 shows the values of weights between hidden layer and output layer obtained during training phase, where the rows correspond to hidden nodes and columns correspond to output nodes. Table 4 shows the bias value at the output node.

Table 1. Weights between input and hidden nodes.

	Node 1	Node 2	Node 3
Node 1	520.26	1743.7	2678.4
Node 2	509.58	462.64	-381.8

Table 2. Bias Values at hidden nodes.

Node 1	0.6004
Node 2	-0.9900
Node 3	13.648

Table 3. Weights between hidden and output nodes.

	Node 1
Node 1	-2.3068
Node 2	1.9983
Node 3	-8.977

Table 4. Bias Value at output node.

Node 1	2.125

The success of training the network can be seen in Figure 6. It can be seen from the figure that the training has properly converged to the goal after 21 epochs. The error of the system is also very less as seen from the performance value which also indicates the proper training of the network. A performance index considered in this work to compare the performance of proposed methods is given by $J = \int_0^t \left(\alpha \cdot \Delta f_1^2 + \beta \cdot \Delta f_2^2 + \Delta P_{tie12}^2\right)$ .The ISE criterion is used because it weighs large errors heavily and small errors lightly. Even though Δf_1 and Δf_2 have very close resemblance, separate weighing factors i.e., α and β are considered for each of them respectively so as to obtain better performance. The parameters α and β are weighing factors which determine the relative penalty attached to the tie-line power error and frequency error. A value of 0.65 has been considered in this work as the value for both α and β. Table 5 shows the comparison of performance of the system when neural controller and integral controller are employed during a laod change of 0.04 p.u MW. It can be seen from the table that the performance of neural controller is far superior than that of integral controller in terms of reduction of overshoot and settling time.

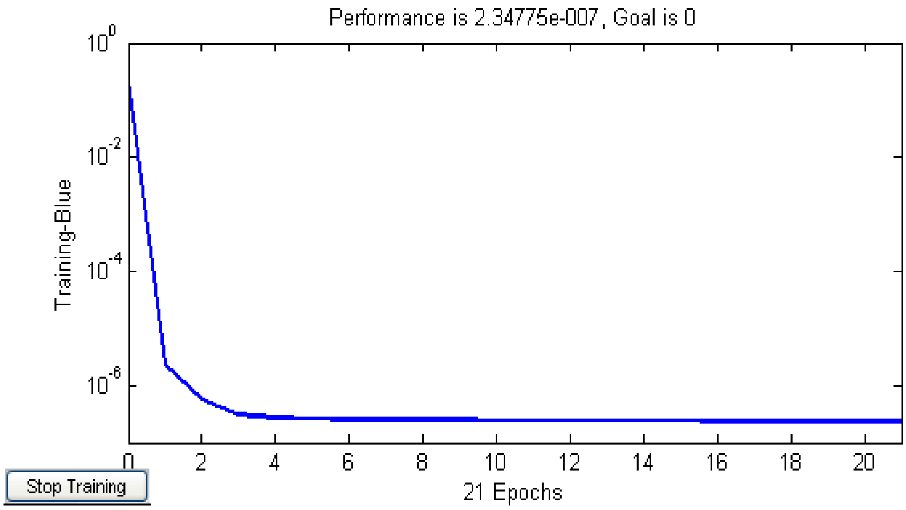

Figure. 6. Training phase of the network

Table 6 shows the comparison of performance index of the system when the neural controller and integral controller are present in the system. It can be observed that the performance index of the system when neural controller is employed is less than the performance index of the system when integral controller is employed. Figure 7 shows the various frequency deviations and tie line power deviations in both the areas during a load change of 0.04p.u MW. It can be observed that neural controller is far superior than the integral controller in terms of peak time, overshoot and settling time in both the areas. Figure 8 shows the comparison between both the controllers in terms of performance index.

Table 5. Comparison of performance of controllers .

	Thermal Area			Hydro Area		
	Peak Time	Overshoot	Settling Time	Peak Time	Overshoot	Settling Time
With Neural Controller	1.985	0.012506	21.75	1.185	0.017814	20.54
With Integral Controller	2.055	0.019635	22.745	1.565	0.023684	21.71
% Improvement	3.40	36.30	4.37	24.28	24.78	5.38

Where % improvement = $\left(\dfrac{\left(\left|With\ Integral\ controller\right| - \left|with\ Neural\ controller\right|\right)}{\left|With\ Integral\ controller\right|}\right) \times 100$

Table 6. Comparison of Performance Index Values.

	Performance Index Value
With Neural Controller	0.0001295
With Integral Controller	0.0002114

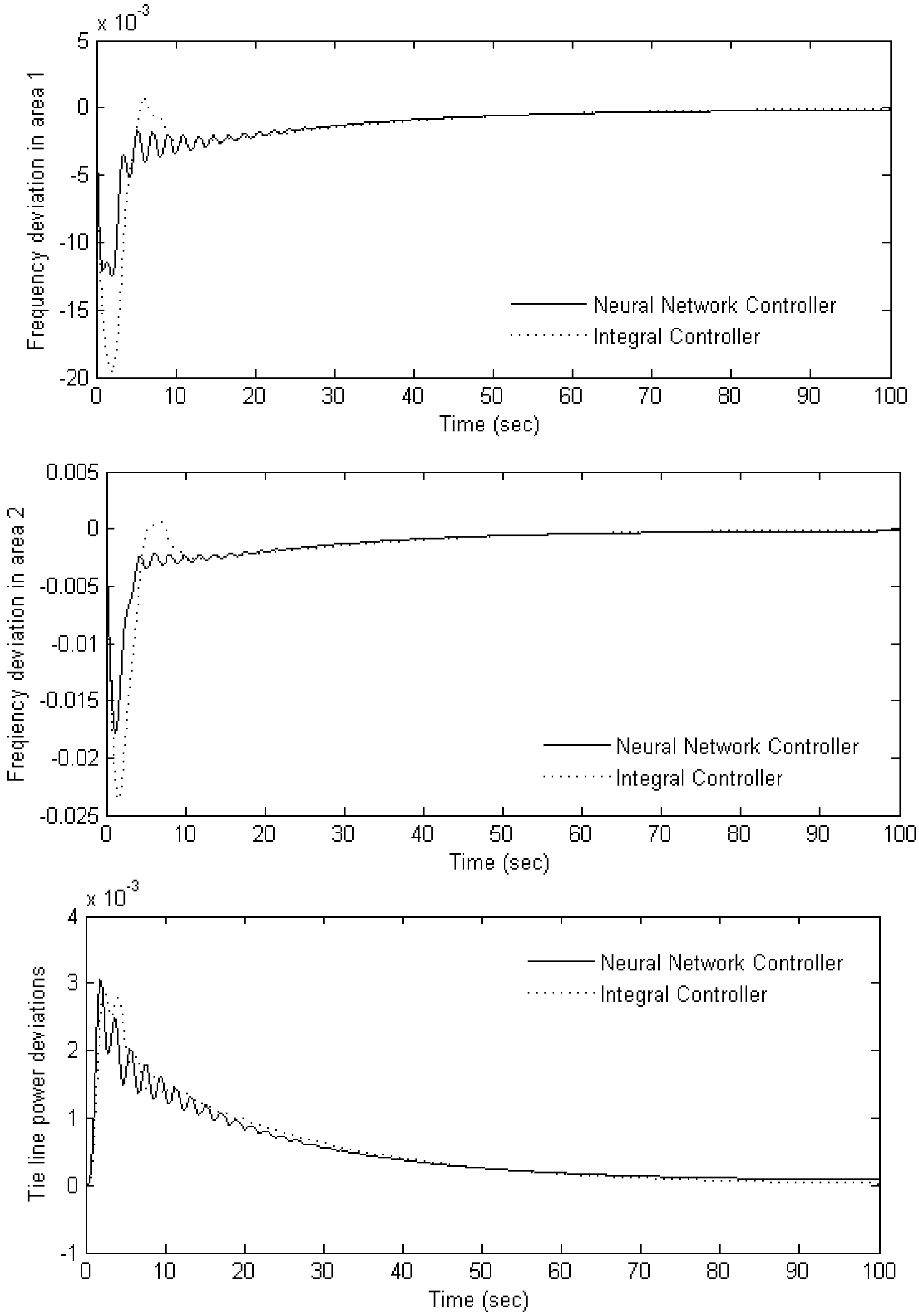

Figure. 7. Frequency and tie line power error deviations in both the areas

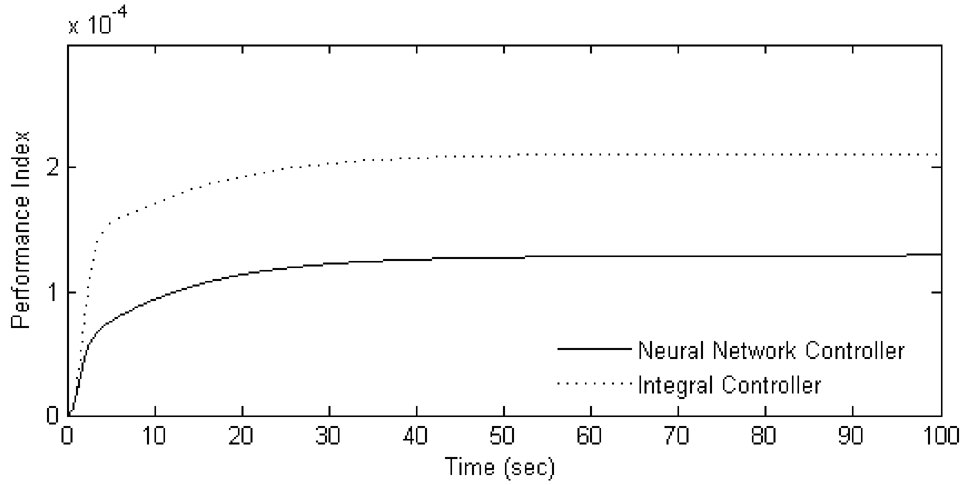

Figure. 8. Comparison of Performance index of the system with both controllers

V. Conclusion

The performance of integral controller and neural controller for a two area hydrothermal system has been investigated. It has been observed that the integral is capable of bringing better dynamic response of the system to some extent. But the conventional design approach requires a deep understanding of the system, exact mathematical models and precise numerical values. The basic feature of neural concept is that the process can be controlled with slight knowledge of its underlying dynamics. The control strategy developed with the help of training mechanism using back propagation algorithm can be employed to bring better dynamic response of the system. The simulation results show the superior performance of the system using neural network controller.

References

[1] C. Concordia and L.K.Kirchmayer, Tie-Line Power and Frequency Control of Electric Power System - Part II, *AIEE Transaction*, vol. 73, Part- 111-A, pp. 133-146, April 1954.

[2] M.L.Kothari, B.L.Kaul and J.Nanda, Automatic Generation Control of Hydro-Thermal system", *journal of Institute of Engineers(India)*, vo1.61, pt EL2, pp85-91, Oct 1980.

[3] J.Nanda, M.L.Kothari, P.S.Satsangi, Automatic Generation Control of an Interconnected hydrothermal system in Continuous and Discrete modes considering Generation Rate Constraints, *IEE Proc*., vol. 130, pt D, No.*1*, pp 455- 460, Jan. 1983

[4] G.A. Chown and R.C.Hartman. Design and experience with a fuzzy logic controller for Automatic generation control, *IEEE Transactions on power systems*, Vol. 13 ,No. 3, pp.965- 970, August 1998

[5] Jawad Talaq and Fadel Al-Basri. Adaptive fuzzy gain scheduling for load frequency control, *IEEE Transactions on power systems*, Vol. 14, pp.145-150, February 1999.

[6] T.P.Imthias Ahamad,P.S. Nagendra Rao and P.S.Sastry, A reinforcement learning approach to automatic generation control, *Electric power systems research 2002(63),* pp.9-26.

[7] Y.L.Karnavas and D.P. Papadopoulos, AGC for autonomous power system using combined intelligent techniques, *Electric power systems research 2002(62*),pp.225-239.

[8] Dynamic Models for steam and Hydro Turbines in Power system studies, *IEEE committee report. Transactions in Power Apparatus & Systems,* Vol.92, No.6, pp.1904-915, Nov./Dec.1973.

Appendix

R =2.4 Hz/p.u.MW; $D = 8.33\times10^{-3}$ p.u. MW/Hz; K_g =1; T_g =0.08 sec; K_t =1; T_t =0.3 sec; K_r =0.5; T_r =10 sec

T_1, T_2, T_R =41.6, 0.513, 5 sec; T_w =1 sec; K_p =120 Hz/p.u. MW; T_p =:20 sec; B =0.425 p.u. MW/Hz