A Novel Control Scheme for Load Frequency Control

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ABSTRACT:

In this paper, a hybrid of Neural Network (NN) and Fast Traversal Filter (FTF) based controller in each area is used to determine the optimal parameters of Load Frequency Control (LFC) of a realistic two area power system. The two area power system is modeled considering the various non -linearities like governor dead band, generation rate constraint (GRC) and boiler dynamics. Input to the controller i.e. the error signal is divided into two parts- linear and non- linear. The linear part of the input signal is minimized by the FTF algorithm, whereas the non- linear part is minimized by the NN algorithm. The output of the controller is the sum of the outputs of NN and FTF networks. The proposed hybrid controller requires less number of samples for training of weights, thus making the system fast. This is highly desirable in power quality problems. The various components of power system are reduced to transfer functions and the system performance is analyzed for 1% step load perturbation in area1 with different controllers- proportional and integral (PI), neural network (NN) and NN+FTF based controllers. The simulations demonstrate the fast and smooth performance of the power system with the proposed controller. Simulated results evince the superiority of the proposed hybrid controller.

KEYWORDS: Automatic Voltage Regulator; Boiler Dynamics; Fast Traversal Filter; Governor dead band; Generation rate constraint (GRC); Load Frequency Control; Particle Swarm Optimization.

1. INTRODUCTION

The main objective of Automatic Load Frequency Control (LFC) is to maintain the frequency and active power change over lines at their scheduled values. As frequency is a common factor throughout the system, any change in active power demand/ generation at power systems is reflected throughout the system by change in frequency. Also, LFC problem is very important in interconnected power system because load perturbation in one area may disturb the frequency of others [1]. The objectives of LFC are met by measuring a control error signal, called the area control error (ACE), which represents the real power imbalance between generation and load [2].

In this paper modeling of a two area thermal power system is done taking into account the boiler system effects, generation rate constraint and the governor dead band effects. Mostly the boiler system effects and the governor dead band effects are neglected in load frequency studies for simplicity and also these investigations are mostly off-line. But, in the realistic analysis of system performance these non-linearities have considerable effects on amplitude and settling time of oscillation and are thus included in this study.

Literature survey shows many investigations in the area of Load Frequency Control and Automatic Voltage Control of single area power system using schemes such as Proportional and Integral (PI) [3], Neural Network (NN) [4], Fuzzy Logic (FL), Genetic Algorithm (GA) [5] and Particle Swarm Optimization (PSO) [6]. The conventional PI control method does not work well for different load conditions as they are fixed type controllers. Fixed gain controllers are designed at nominal operating conditions and fail to provide best control over wide range of operating conditions. The active and reactive power demands are never steady and they continuously change with load demand. The PI controllers can take care of small changes in load demand without frequency and voltage exceeding the prescribed limit. In PI controller, proportionality constant provides simplicity, reliability, directness etc. But it does not provide adequate control performance when system non-linearities and boiler dynamics are considered [2-4] or if some kind of disturbance acts on the system. Training of neural network and membership functions of fuzzy logic require a large number of input-output samples, hence increasing the mathematical complexity. Although, PSO is population-based search approach, but it requires large data for training the weights and involves highly complex mathematical operations [5]. Also global optimization may take large number of iterations.

To overcome the shortcomings of the above mentioned controllers, a novel approach is proposed, i.e. hybrid of Neural Network (NN) and Fast Traversal Filter (FTF) based controller for LFC and AVR systems. This controller requires less memory and less number of samples for training, thus making the system fast (i.e. small settling time). This scheme also corroborates improved performance in short possible time (i.e. small settling times), hence making the system computationally efficient.

Analysis of dynamic responses such as frequency deviation in area 1 (ΔF1), area 2 (ΔF2) and tie line power deviation (ΔPtie), considering 1% step load perturbation in area 1 of system, with different controllers. The response of different controllers analyzed are Proportional and Integral (PI), on-line Neural Network (NN) and combination of NN and FTF controller. To the best of authors knowledge, no work has been reported in the literature of LFC with a hybrid of NN and FTF controller for such a realistic power system which considers various system nonlinearities. The novelty of the paper is that a comprehensive comparison of these controllers (PI, NN, NN+FTF) is done considering most of the system non-linearities.

The paper is organized as follows: Section II focuses on the proposed controller, Section III deals with modeling of load frequency control. Section IV gives simulation results and finally Section V presents the conclusion.

2. THE PROPOSED CONTROLLER

Please There two main objectives of LFC are maintaining frequency and tie line power exchanges at scheduled values. Their variations are weighted together by a linear combination to a single variable called the area control error (ACE). ACE represents the real power imbalance between generation and load. Input to the controller is Area control error (ACE) and change in area control error (AĊE) as given by equation (1).

$$\left.\begin{aligned} u(k) &= u_1(k) + u_2(k) \\ ACE_i(k) &= X_i(k) = \Delta F_i(k) \times B_i + \Delta P_{tie}(k) \\ A\dot{C}E_i(k) &= ACE_i(k) - ACE_i(k-1) \end{aligned}\right\} \quad (1)$$

where: i is number of areas in power system under study,

X_i is input to the controller of ith area,

ΔF is change in frequency,

B is frequency bias constant,

ΔP_{tie} is change in tie line power.

In the nascent approach, the input signal to the controller is divided into linear and non- linear part. Using FTF algorithm for the linear part and neural network for the non- linear part of the error signal, an efficient controller is developed to achieve faster convergence of weights and the least square of error with a small number of samples [7]. Figure 1 shows the block diagram of the proposed controller, i.e. NN+FTF based controller. Set point and error signal are inputs to the FTF part of the controller whereas; error signal is input to the NN part of the controller. This concept originates from the fact that the non- linear part of the signal tries to adhere to the set point(r) and the linear part (e) tries to maintain the linearity between the two consecutive points. The output of the controller is the sum of the outputs of the non-linear block i.e. neural network (u_1) and the linear block (u_2).

The two parts of the controller are explained as follows:

2.1. Fast Transversal Filter (FTF)

As clear from the name transversal FTF makes use of the combination of four separate nth order filters in unison. These filters are denoted by[9]:

1) $w_n(n)$, Least squares (LS) prediction filter
2) $f_n(n)$, forward prediction error filter
3) $b_n(n)$, backward prediction error filter
4) $g_n(n)$, gain filter

These filters are the direct consequence of:

a) Requiring the LS prediction filter to be $w_n(n)$ transversal in nature.

b) Maintaining the required LS orthogonal conditions at both times n-1 and n.

In predicting LS, the LS error criterion is used to optimally predict the desired signal using the required data. Prediction should be done with a transversal filter structure. The second LS transversal filter used in FTF algorithm is an nth order forward linear prediction filter. This filter computes the Forward Prediction Error (FPE) between the current data vector $x(n)$ and a prediction $x_f(n)$ based on the knowledge of past data vectors. The third transversal filter is an nth order backward filter. This computes the Backward Prediction Error *(BPE)* between the current data vector $x(n)$ and a prediction $x_b(n)$ based upon the future data vectors. The last one is the Gain Traversal Filter $g_n(n)$. In general, it can be said that these four filters and other scalar parameters are all a natural consequence of minimizing the original LS error. Equations for FTF algorithm are given in appendix I.

The output of the FTF algorithm block, $u_2(k)$ is given by

$$u_2(k) = w_{f1} \times r(k) + w_{f2} \times r(k-1) \quad (2)$$

where, w_{f1} and w_{f2} are the FTF weights to be updated so as to minimize error. Two weights are taken because output depends on present input and past input.

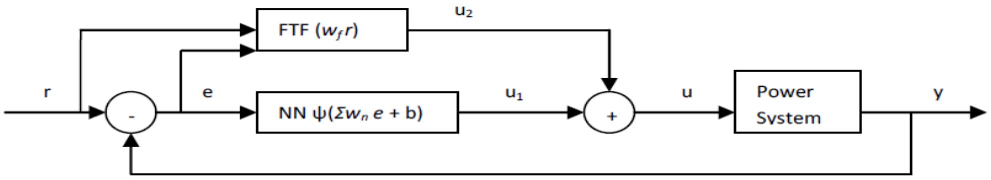

Fig. 1. Biock diagram of the proposed controller

2.2. Neural Network (NN)

A three layered feed- forward neural network is used.

Input to neural network is *X(k)* as given in equation 1.The output of the NN, $u_1(k)$ is:

$$u_1 = \varphi[\sum_{k=0}^{n} w_k X_k + b] \tag{3}$$

where, *n* is the number of samples taken at a time,
w_k are the weights of the neural network,
b is the bias,
u_1 is the output of the NN controller.

The weights of the NN are adjusted by gradient descent and back propagation algorithms. As in figure 1, the output of FTF controller (u_2) and NN controller (u_1) add to give the final output of the proposed controller(*u*).

Thus, the output of the controller *u(k)* is:

$$u(k) = u_1(k) + u_2(k) \tag{4}$$

3. LOAD FREQUENCY CONTROL (LFC) WITH PROPOSED CONTROLLER

The realistic two area interconnected Power system simulated in this study is shown in Fig.2 which comprises of two single area thermal systems, connected through a power tie line. Each area feeds its user pool and tie line allows electric power to flow between the areas. The system is modeled incorporating governor dead band, generation rate constraint (GRC) non-linearities and boiler dynamics [8]. Each component of the power system is reduced to its transfer function as shown in figure 2. The dynamic model of thermal systems with the mentioned nonlinearities is described in [8]. Furthermore, in the new environment, both the PI controllers are replaced by neural network and then by hybrid of NN and FTF. These controllers are trained on line.

The various non linearities considered are discussed as follows:

3.1. Governor Dead Band

Governor Dead Band (GDB) is defined as the total magnitude of a sustained speed change within which there is no resulting change in valve position. Describing function approach is used to incorporate the governor dead band non-linearity. Derivation for its transfer function can be seen in [8].

3.2. Generation Rate Constraint (GRC)

In practice, there exists a maximum limit on the rate of change in the generating power. For thermal system a generating rate limitation of 0.1 p.u. MW per minute is considered.

3.3. Boiler Dynamics

An oil or gas fired drum type boiler system is modeled in this study. The boiler receives feed water which has been preheated in the economizer and provides saturated steam outflow. Recirculation boiler make use of a drum to separate steam flow from the recirculation water so that it can proceed to the super heater as a heatable vapour; hence recirculation boiler are referred to as drum type boiler. Figure 3 shows the simulink model of boiler dynamics.

The whole two area power system is reduced to transfer functions. Values of different parameters are in appendix II.1% step load perturbation is given in area 1 as disturbance to the system and changes in frequency in each area and change in tie line power are computed.

Under steady state condition, change in tie line power and change in frequency of each area should converge to zero. The objective function to be minimized by the controller is

$$J = \int_0^t (\Delta F_1^2 + \Delta F_2^2 + \Delta P_{tie}^2) dt \tag{5}$$

The whole one iteration is shown in figure 4a. As seen in the figure the input X_i is computed and becomes input to the proposed controller. The output of the controller is fed in area system with 1% step load perturbation in area 1 at time =1 second. Performance index *J* is computed; the weights and membership functions are updated by the new values. Values of objective function (*J*) and the new values of ΔF_1, ΔF_2 , ΔP_{tie} are computed. The corresponding weight *w(k,i)* should be increased in direct proportion to the output error because the error is caused by the weight. Online training of weights and parameters of FTF and NN is done using, back propagation and gradient descent algorithms respectively. Then output of the controller is computed using these new values of ΔF_1, ΔF_2 , ΔP_{tie} as inputs. This completes one cycle. This is repeated till the objective function is reduced to a minimum value (0.001). Now again new value of input is computed feed to the proposed controller with these new values. This is repeated till steady state error reduces to a minimum value (0.001). Subsystem for the proposed controller is shown in figure 5(a).

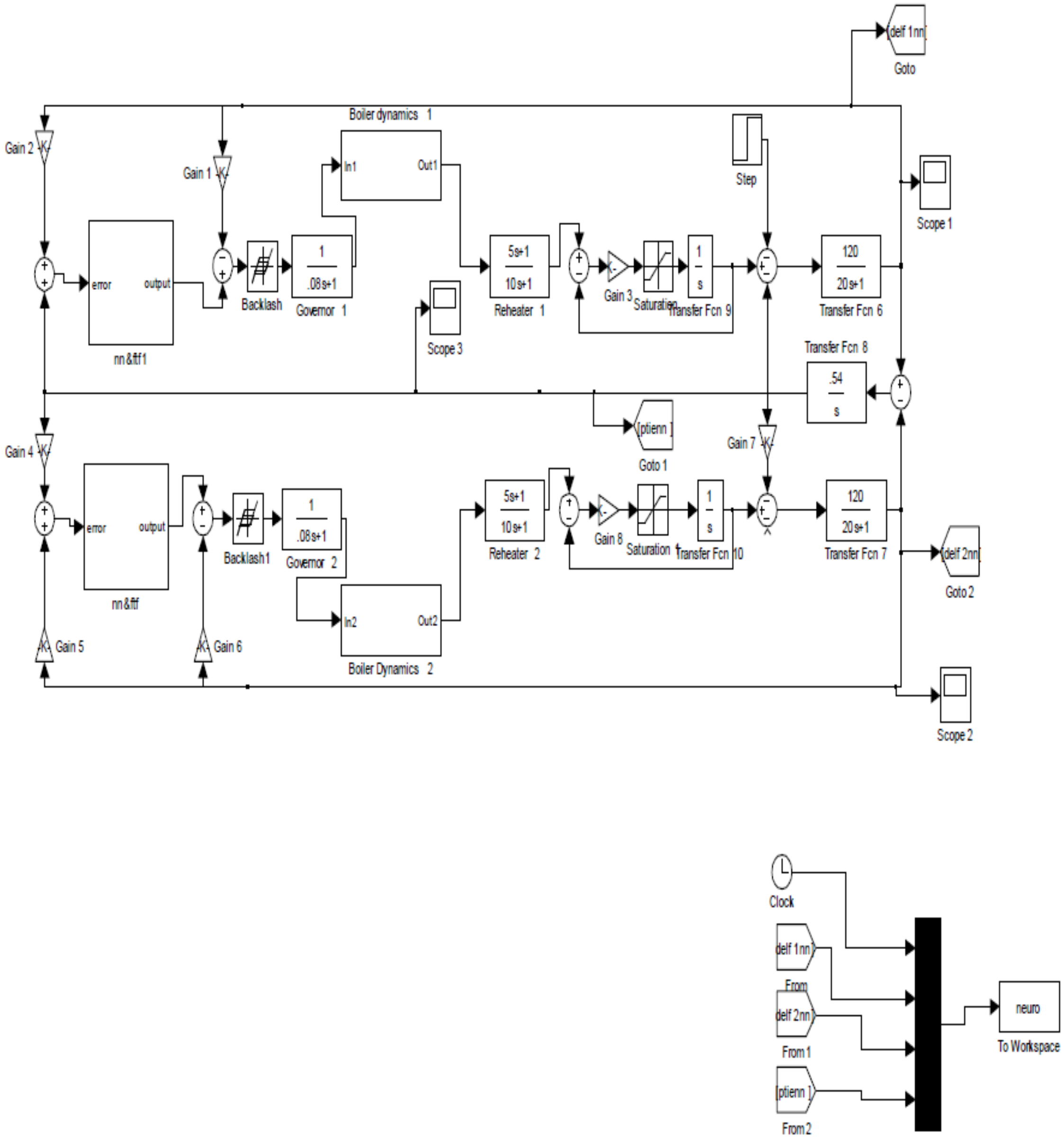

Fig. 2. Transfer Function modeling of a two area thermal system

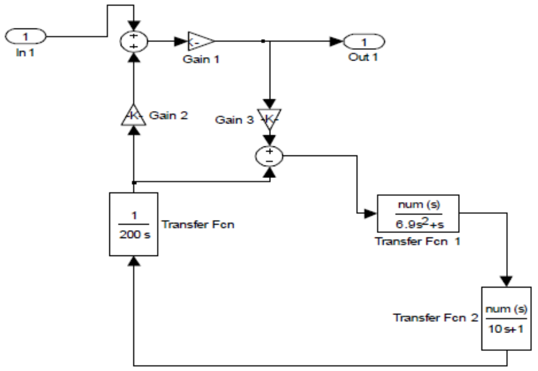

Fig. 3. Boiler dynamics

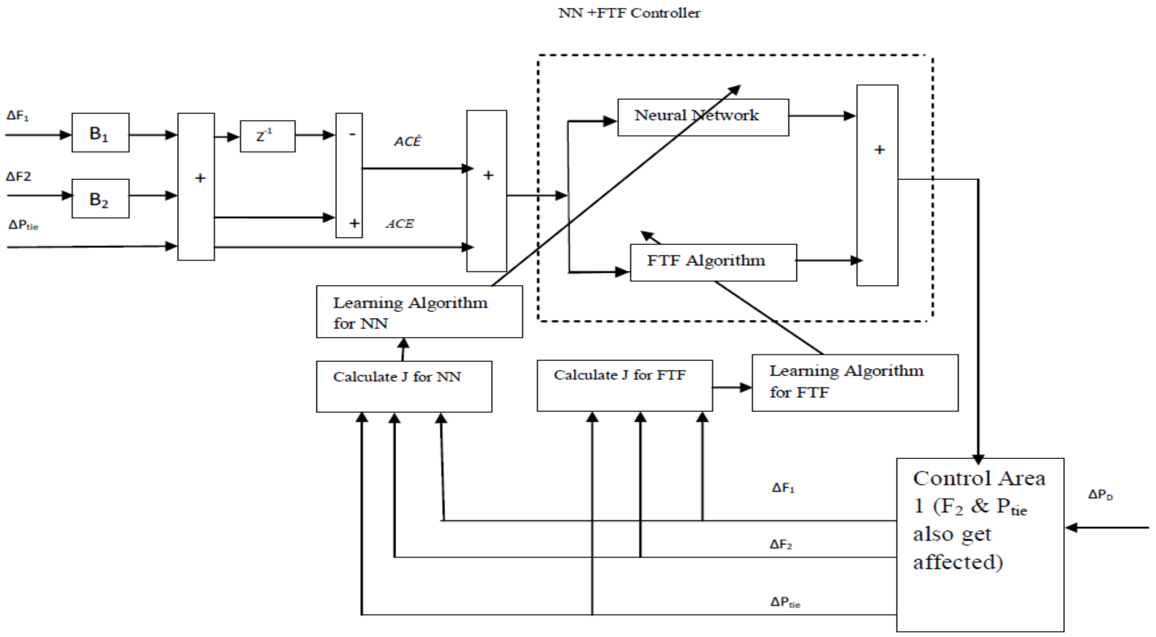

Fig. 4. The proposed controller showing one complete iteration

Error in actual and reference frequency is the input to the neural controller subsystem and error and reference frequency are inputs to the FTF controller subsystem as shown in figure 5(a). MATLAB function along with a bus system is used in the simulink model of FTF controller which is shown in figure 5(b). Error, derivative of error, reference frequency and ramp function are the inputs to the MATLAB function block linked to m file of FTF algorithm and its output are weights of the filter. Output u2 is the product of weights and reference value. Embedded MATLAB function used in the simulink model of Neural Network is shown in figure 5(c). Three layer feed forward neural network is used. Initial weights (w_1, w_2) and biases (b_1, b_2) are randomly initialized. These are update to new weights (w_{11}, w_{22}) and biases (b_{11},b_{22}) by using back propagation algorithm.

A similar type of NN and FTF based controller is designed for area 2. Due to similarity in nature it is not discussed here.

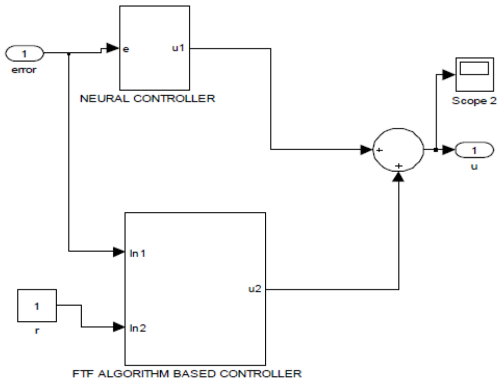

Fig. 5(a). Simulink model for the proposed controller sub-system

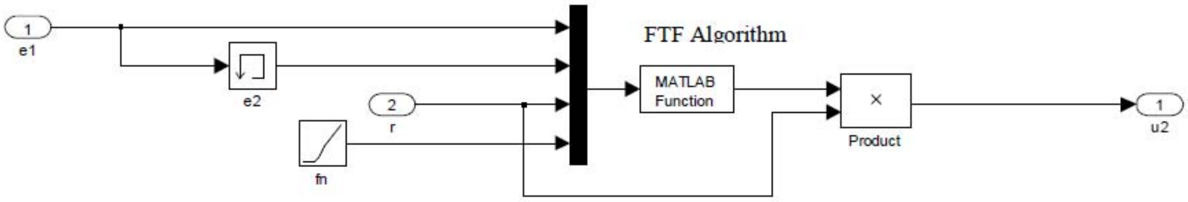

Fig. 5(b). Simulink subsystem for FTF controller

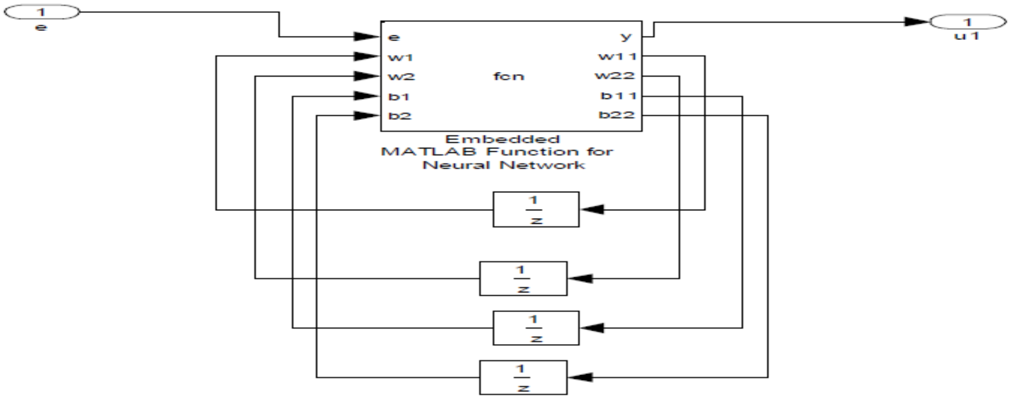

Fig. 5(c). Simulink subsystem for neural controller

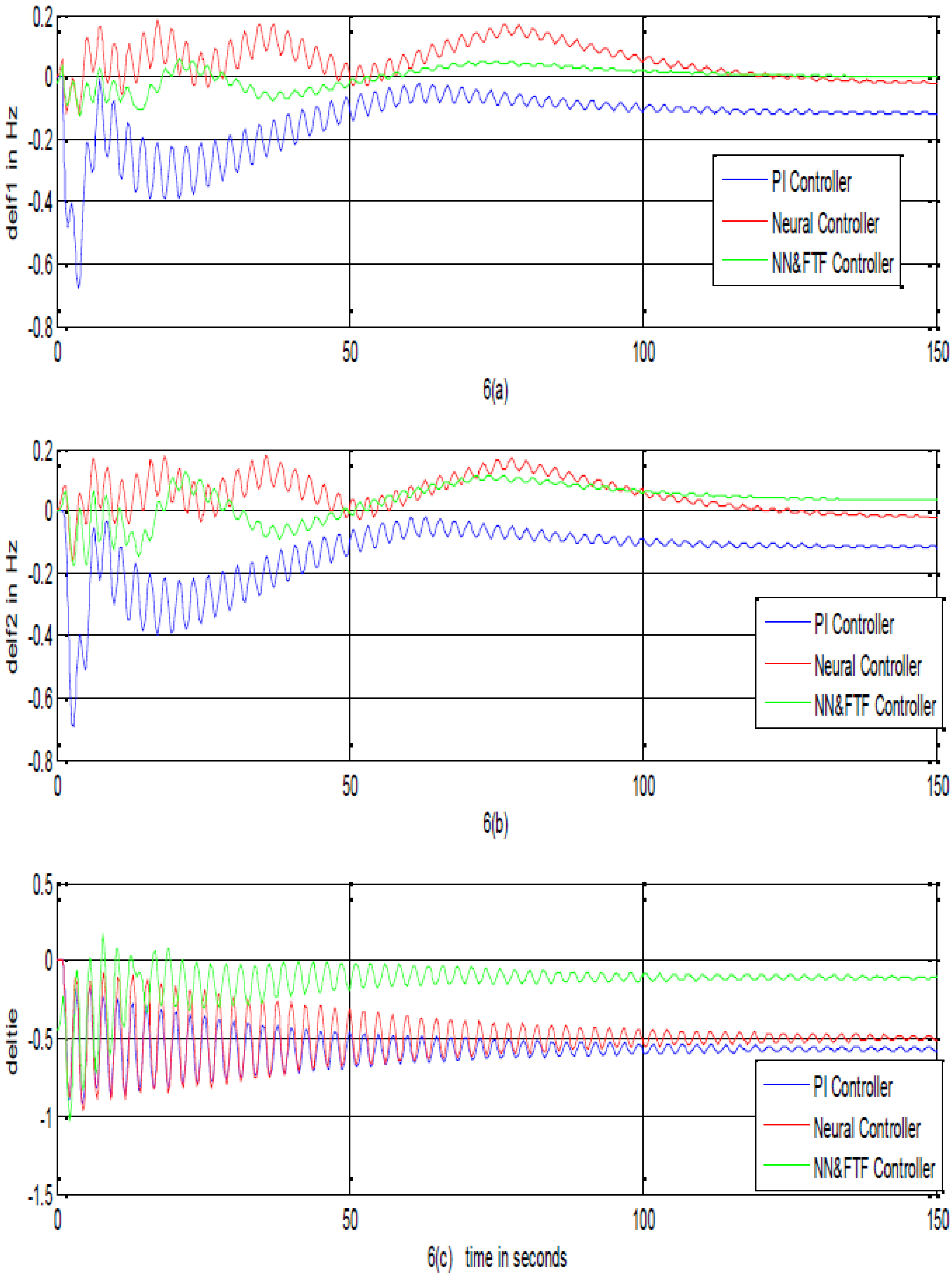

Fig. 6(a). Frequency deviation in area 1(Hz),6(b) Frequency deviation in area2(Hz),6(c)Deviation in tie power (PUMW)

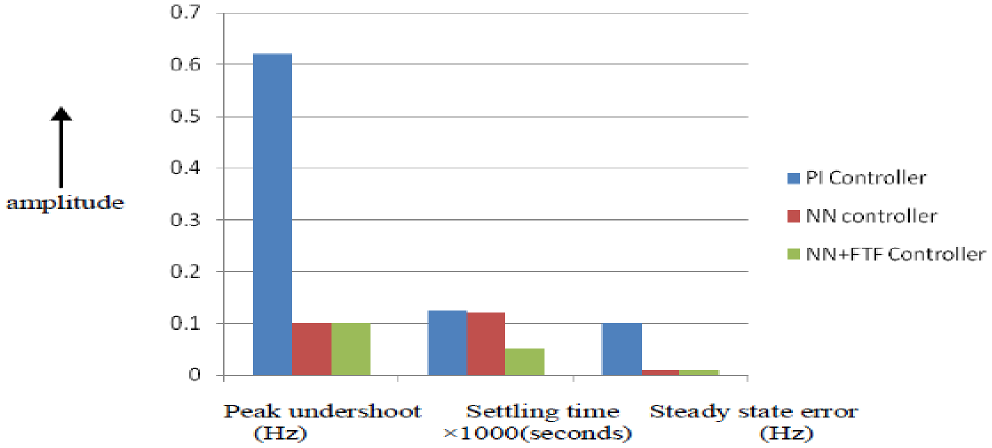

Fig. 7. Comparative analysis of different controllers for Δf_1

4. SIMULATION RESULTS

A comparative study of frequency deviation in area 1 (ΔF_1) is plotted in figure 6(a), frequency deviation in area 2 (ΔF_2) in figure (b) and tie line power deviation (ΔP_{tie}) in figure 6(c) for 1% step load perturbation in area 1 of the system for different type of controllers(PI, NN, NN+FTF). This study uses ACE as error signal to control the frequency of a power system. From figure 6 it is observed that the proposed on line controller exhibits very good performance having smaller overshoot and steady state errors. Figure 7 shows the bar graph for comparison of different controllers when simulated for ΔF1. The bar graph clearly shows that the proposed controller gives the least values for peak overshoot, settling time and steady state error. Peak overshoot decreases to approximately 83% as compared to PI and is nearly same as compared to on line NN controller. Reduction in settling time and steady state is remarkable with the proposed controller. Settling time reduces by 60% when NN+FTF controller is compared with PI and by 56% when compared with NN controller. Steady state error also reduces by 90% when NN+FTF controller is compared with PI and is nearly same when compared with NN controller. Dynamic response with the proposed controller is greatly improved as compared to PI for all the three measures (Peak undershoot, settling time & steady state error). When compared with on line NN controller though there is no remarkable reduction in peak undershoot and steady state error, but there is drastic reduction in settling time. This is highly desirable in power quality problems. Simulation results agree with the theory of the proposed controller i.e. proposed hybrid controller requires less number of samples for training of weights, thus making the system fast.

Table 1. Comparative Study of Dynamic Response

	Peak undershoot (Hz)	Settling time (sec)	Steady state error (Hz)
FREQUENCY DEVIATION IN AREA 1 (ΔF_1)			
PI Controller	0.62	125	0.1
Neural Controller	0.1	120	0.01
Proposed controller	0.1	50	0.001
FREQUENCY DEVIATION IN AREA 2 (ΔF_2)			
PI Controller	0.7	100	0.15
Neural Controller	**0.17**	105	0.02
Proposed controller	0.17	100	0.01
TIE LINE POWER DEVIATION (ΔP_{TIE})			
PI Controller	0.95	75	0.55
Neural Controller	0.9	70	0.5
Proposed controller	1.0	60	0.05

Detailed comparison of the dynamic responses of the various controllers is shown in table I. The simulation results proved that proposed controller is robust in its operation and gives good damping performance both for frequency and tie line power deviation compared to conventional PI as well as neural counterpart as clear in table I. Besides the simple architecture of the controller it has the potentiality of implementation in a real time environment.

Simulated results clearly show that the proposed controller exhibits relatively good performances with smaller overshoot, lesser steady state error and settling time, in the response curves of frequency deviations of area 1 and 2 and tie line power deviations. It is seen that oscillatory response is reduced with NN+FTF controller as compared to PI and NN controller.

5. CONCLUSION

In the paper a novel approach of hybrid NN and FTF based controller is proposed to make the dynamic response of load frequency faster and smoother in a two area realistic power system. The effect of the various non -linearities like governor dead band, generation rate constraint (GRC) and boiler dynamics are considered. The conventional controllers like PI, on line neural used have large peak overshoot, settling time and steady state error. In the nascent approach, the input signal to the controller is divided into linear and non- linear part. Using FTF algorithm for the linear part and neural network for the non- linear part of the error signal, an efficient controller is developed to achieve faster convergence of weights. The proposed scheme is superior compared to the PI and online NN based controller in terms of improved damping and set point tracking. The increased damping is highly desirable as it enhances the ride-through capability of sensitive loads and processes. Moreover, control action is very smooth, which means less strain on the control circuitry.

6. APPENDIX

Appendix I

FTF Algorithm

It consists of the following steps:

Initialize:

$$b_N(0) = f_N(0) = w_f(0) = c_N(0) = 0$$

$\gamma_N(0) = 1.0 \quad \varepsilon^f(0) = \varepsilon^b(0) = \delta,$ small positive constant.

Iterate:

For *n*=1 to *n*, do:

$$e^f(n/n-1) = x(n) - x_N^T(n-1) f_N(n-1)$$

$$e^f(n/n) = \gamma_N(n-1) e^f(n/n-1)$$

$$\varepsilon^f(n) = \varepsilon^f(n-1) + e^f(n/n) e^f(n/n-1)$$

$$f_N(n) = f_N(n-1) + e^f(n/n) c_N(n-1)$$

$$\gamma_{N+1}(n) = \frac{\varepsilon^f(n-1)}{\varepsilon^f(n)} \gamma_N(n-1)$$

$$\begin{bmatrix} m_N(n) \\ m(n) \end{bmatrix} = \begin{bmatrix} 0 \\ c_N(n-1) \end{bmatrix} + \frac{e^f(n/n)}{\varepsilon^f(n-1)} \begin{bmatrix} 1 \\ -f_N(n-1) \end{bmatrix}$$

$$e^b(n/n-1) = m(n)\varepsilon^b(n-1)$$

$$\gamma_N(n) = [1 - \gamma_{N+1}(n) m(n) \varepsilon^b(n-1)]^{-1} \gamma_{N+1}(n)$$

$$e^b(n/n) = \gamma_N(n) e^b(n/n-1)$$

$$\varepsilon^b(n) = \varepsilon^b(n-1) + \varepsilon^b(n/n) e^b(n/n-1)$$

$$c_N(n) = m_N(n) + m(n) b_N(n-1)$$

$$b_N(n) = b_N(n-1) + c_N(n) e^b(n/n)$$

Extend to the joint process

$$e(n/n-1) = d(n) - x_N^T(n) w_f(n)$$

$$e(n/n) = \gamma_N(n) e(n/n-1)$$

$$w_f(n) = w_f(n-1) + c_N(n) e(n/n)$$

where, $b_N(n)$ is the backward prediction filter,

$f_N(n)$ is the forward prediction filter,

$w_f(n)$ is the least square prediction filter,

$c_N(n)$ is the gain vector,

$\gamma_N(n)$ is the angle update parameter,

$e^f(n/n)$ is the forward prediction error (FPE),

$e^b(n/n)$ is the backward prediction error (BPE),

$\varepsilon^f(n)$ is the forward prediction error (FPE) residual or the energy of the FPE vector $e^f(n/n)$ i.e.

$\langle e^f(n/n), e^f(n/n) \rangle$,

$\varepsilon^b(n)$ is the backward prediction error (BPE) residual or the energy of the BPE vector $e^b(n/n)$ i.e.

$\langle e^b(n/n), e^b(n/n) \rangle$,

$e(n/n)$ is the error,

$x_N^T(n)$ is the input vector,

$d(n)$ is the desired output vector.

Appendix II

For Figure 2

P_{ri} =2000 MW, T_{ti}=0.3s, K_{pi}=120Hz/puMW, T_{gi}=0.08s , K_{ri}=0.5 ,T_{ri}=10s, T_{pi}=20 s ,T~~12~~=0.086 , R_i =2.4 Hz/ pu MW,

f=60 Hz, Bi =0.425 pu MW/Hz,i= 1 & 2

In neural controller 3 layer MLFFN is used. Weights are initialized to zero and back-propagation and gradient descent are used for training of weights.

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