CHAPTER 5
A NOVEL CONTROL SCHEME FOR LOAD FREQUENCY CONTROL

In this chapter, 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 as modeled in section 4.1 considering the various non-linearities like governor dead band, generation rate constraint (GRC) and boiler dynamics is considered. Importance of load frequency control and modeling of two area power system considering the system non linearities has already been discussed in chapter 4. To overcome the shortcomings of the conventional controllers (referred in chapter 4), a novel approach is proposed, i.e. hybrid of Neural Network (NN) and Fast Traversal Filter (FTF) based controller for LFC and AVR systems. Input to the controller i.e. the error signal is divided into two parts- linear and non-linear. The linear part of the error 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 reason behind the error signal being divided is explained as follows:

If sampling time of any signal is large it implies less number of samples. With few samples quality of signal approximation is bad. This is because non-linearity of signal is unachievable and linearity dominates. On other hand small sampling time implies that there are large numbers of samples. In this situation, non-linearity predominates over linearity between the two consecutive samples. The signal approximation is good with large number of weights but response is slow. The proposed technique solves the problem of large number of weights and slow response of the system. In this the desired signal is chopped into small sets. The chopping exclusively belongs to the user requirement. These sets when combined again then form the original desired signal. The chopped signal consists of less number of samples and it has dominating linearity in addition to non-linearity. We have chosen FTF algorithm for the linear part and NN for non-linear part.

Thus 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 area 1 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 show the superiority of the proposed hybrid controller. 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 one ($\Delta F_1$), area two ($\Delta F_2$) and tie line power deviation ($\Delta P_{tie}$), considering 1% step load perturbation in area 1 of system, with different controllers has been done. 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 chapter is organized as follows: Section 5.1 focuses on the proposed controller. Section 5.2 gives simulation results and finally Section 5.3 presents the conclusion.

5.1 THE PROPOSED CONTROLLER

The two main objectives of LFC are maintaining, frequency and tie line power exchanges at their 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 ($A\dot{C}E$) as given by equation (5.1).

\[
\begin{align*}
    u(k) &= u_1(k) + u_2(k) \\
    ACE_i(k) &= X_i(k) = \Delta F_i(k) \times B_i + \Delta P_{tie}(k) \\
    A\dot{C}E_i(k) &= ACE_i(k) - ACE_i(k-1)
\end{align*}
\]

(5.1)

where:
- $i=2$ is number of areas in power system under study,
- $X_i$ is input to the controller of $i$th area,
- $\Delta F$ is change in frequency,
\( B \) is frequency bias constant, 
\( \Delta P_{tie} \) is change in tie line power.

In the present 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 small number of samples [105]. Figure 5.1 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:

5.1.1. 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:

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 \( g_t(n) \). 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 C.

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

\[
u_2(k) = w_{f1} \times r(k) + w_{f2} \times r(k-1) \tag{5.2}\]

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[106].

5.1.2. Neural Network (NN)

A three layered feed-forward neural network is used.

Input to neural network is \( x(k) \) as given in 5.5. The output of the NN, \( u_f(k) \) is:

\[
u_1(k) = \varphi[\sum_{k=0}^{n} w_k x_k + b] \tag{5.3}\]

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 back propagation algorithm. As in figure 5.1, 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:

\[
u(k) = u_1(k) + u_2(k) \tag{5.4}\]
The whole structure is shown in figure 5.2. 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 $\Delta F_1$, $\Delta F_2$, $\Delta P_{tie}$ are computed. The corresponding weight $w(k,i)$ is 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. Then output of the controller is computed using these new values of $\Delta F_1$, $\Delta F_2$, $\Delta P_{tie}$ as inputs. This completes one cycle. Now again new value of input is computed fed to the proposed controller with these new values. This is repeated till steady state error reduces to a minimum value. Subsystem for the proposed controller is shown in figure 5.3(a). 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 5.3(a). MATLAB function along with a bus system is used in the simulink model of FTF controller which is shown in figure 5.3(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 $u_2$ is the product of weights and reference value.
Fig. 5.2. The proposed controller showing complete structure.

Embedded MATLAB function used in the simulink model of Neural Network is shown in figure 5.3(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 updated to new weights \( w_{11}, w_{22} \) and biases \( b_{11}, b_{22} \) by using back propagation algorithm.

A similar NN and FTF based controller is designed for area two.

5.2 SIMULATION AND RESULTS

A comparative study of frequency deviation in area one \( (\Delta F_1) \) is plotted in figure 5.4(a), frequency deviation in area 2 \( (\Delta F_2) \) in figure 5.4(b) and tie line power deviation \( (\Delta P_{tie}) \) in figure 5.4(c) for 1% step load perturbation in area one of the system for different type of controllers(PI, NN, NN+FTF). This study uses ACE as error signal to control the frequency of the power system.
Fig. 5.3(a). Simulink model for the proposed controller sub-system.

Fig. 5.3(b). Simulink subsystem for FTF controller.

Fig. 5.3(c). Simulink subsystem for neural controller.
From figure 5.4 it is observed that the proposed on line controller exhibits very good performance with smaller overshoot and steady state errors. Figure 5.5 shows the bar graph for comparison of different controllers when simulated for $\Delta F_1$.

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, there is a 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.

Detailed comparison of the dynamic responses of various controllers is shown in table 5.1. 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 network as clear in table 5.1. 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.
Fig. 5.4(a). Frequency deviation in area 1(Hz), 5.4(b). Frequency deviation in area2(Hz), 5.4(c). Deviation in tie line power (PU MW).
Fig. 5.5. Comparative analysis of different controllers for $\Delta F_1$.

<table>
<thead>
<tr>
<th></th>
<th>Peak undershoot (Hz)</th>
<th>Settling time (sec)</th>
<th>Steady state error (Hz)</th>
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</thead>
<tbody>
<tr>
<td><strong>Frequency Deviation In Area 1 ($\Delta F_1$)</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>PI Controller</td>
<td>0.62</td>
<td>125</td>
<td>0.1</td>
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<tr>
<td>Neural Controller</td>
<td>0.1</td>
<td>120</td>
<td>0.01</td>
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<tr>
<td>Proposed controller</td>
<td>0.1</td>
<td>50</td>
<td>0.001</td>
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<td><strong>Frequency Deviation In Area 2 ($\Delta F_2$)</strong></td>
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<td>PI Controller</td>
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<td>0.15</td>
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<tr>
<td>Neural Controller</td>
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<td>105</td>
<td>0.02</td>
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<tr>
<td>Proposed controller</td>
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<td>100</td>
<td>0.01</td>
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### Tie Line Power Deviation ($\Delta p_{\text{tie}}$)

<table>
<thead>
<tr>
<th>Controller</th>
<th>$\Delta p_{\text{tie}}$</th>
<th>$t_s$</th>
<th>$\Delta E_{\text{SS}}$</th>
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<tbody>
<tr>
<td>PI Controller</td>
<td>0.95</td>
<td>75</td>
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<tr>
<td>Neural Controller</td>
<td>0.9</td>
<td>70</td>
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<td>Proposed controller</td>
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<td>0.05</td>
</tr>
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</table>

#### 5.3 CONCLUSION

In the chapter 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 and on line neural used have large peak overshoot, settling time and steady state error. In the current 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 as compared to the PI and NN 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.