MULTILAYER PERCEPTRON FEEDFORWARD NEURAL NETWORK BASED POWER SYSTEM STABILIZER FOR EXCITATION CONTROL SYSTEM

Suhail Khokhar* Aslam P. Memon** M. Usman Keerio**

ABSTRACT

Electrical power system (EPS) is becoming more complex and non-linear due to its varying operating conditions. In order to keep EPS in the steady state condition, active power (P) or terminal voltage (V_t) and reactive power (Q) or frequency (f) must be controlled and maintained continuously. The response of the transient stability (terminal voltage) can be improved by adopting suitable controller as an additional voltage controller with the automatic voltage regulator (AVR) in the excitation system, whereas the dynamic stability (frequency deviations i.e $\Delta\omega$) can be enhanced with governing system. In power system networks, low frequency oscillations have become a major concern for many years. In order to depress low frequency oscillation, the power system stabilizer (PSS) parameters must be adjusted when there are changes in power system network conditions. This paper presents the application of multilayer perceptron feedforward neural network (MLPFFNN) as a controller to tune PSS parameters for achieving better enhancement in stability. For training MLP neural network, real power (P) and reactive power (Q) of synchronous machine are chosen as the input signals and the output are; the desired power network stabilizer parameters. The proposed controller is implemented as single machine connected at infinite bus (SMIB) and compared with conventional controllers using Matlab/Simulink. The results obtained show the promising results due to the improvement in terminal voltage (V_t) as well as frequency deviation ($\Delta\omega$).

Keywords: ***Synchronous generator, Power system stabilizer, Feedforward neural networks, Multilayer perceptron, Transient and dynamic stability, Matlab/simulink.***

1. INTRODUCTION

The control of active power and reactive power is very important to maintain the system in steady state condition [1]. The excitation system of the synchronous generator with automatic voltage regulator (AVR) controls the generated electromotive force (emf) and therefore maintains not only the reactive power flow but the power factor and current magnitude as well. The governor together with load frequency control (LFC) regulates the frequency of the generator and maintains the real power [2-8].

The power network is always complex and nonlinear due to continuously variation of loading conditions and is being subjected to small perturbations. The modern fast acting, high gain automatic voltage regulators (AVR) cause the poor oscillations or damping characteristics which deviate the rotor angle of the generator (δ).

These high gain AVRs cause a large phase lag at low system frequencies which are greater than the excitation system frequency. Therefore AVR has an important effect of minimizing synchronizing torque during sudden disturbances but it affects the damping torque negatively [3-8].

In power system networks, damping torque or low

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frequency oscillations become a major concern for many years. To offset this effect and to improve the system damping in general, a new signal producing torques in phase with the rotor speed are introduced. This supplementary stabilizing signal is known as "Power System Stabilizer (PSS)" of network. In order to depress low frequency oscillation, the power system stabilizer parameters must be adjusted when there are changes in power network conditions.

Various techniques of PSS parameters based on optimal variable structure control (OVSC), adaptive control (AC), and intelligent controls have been proposed to design PSS [9-15]. The artificial intelligent (AI) methods such as genetic algorithm G.A), simulated Annealing, Tabu Search, evolutionary programming and multi agent particle swarm optimization (MAPSO) for obtaining PSS parameters [16-20], self-tuning PSS [21], PI, PID, and Fuzzy based PSS [22-24], and Fuzzy set and NNs [25] are also suggested in literature.

These conventional power system stabilizers possess fix parameters and operate at particular loading conditions. These PSSs need tuning in case of changing loading conditions. The main limitation of such PSS is that it takes a large amount of computing time for on-line parameter identification and also need knowledge based, and membership functions which are defined off-line, and kept unchanged during the online operation.

For this problem, we need a power system stabilizer, which should possess self-learning, adaptation, approximation and artificial intelligence properties of handling the changes and uncertainties in the system in on and off-lines.

The neural network (NN) possesses great prospective capabilities because they have been developed on logical mathematical formulation and versatile and well-known mathematical back grounds [26].

Due to these problems an artificial neural network based PSS is proposed by taking angular frequency as an input to improve the transient and dynamic stability of electrical power system.

Feedforward multilayer perceptron (MLP) neural network with back propagation (BP) algorithms based PSS is proposed in this paper. The simulations results using Matlab/Simulink and neural network toolbox are compared with conventional, PID and proposed PSS. The applicability and suitability of the proposed PSS are investigated and the improvements in transient & steady state stability enhancement are discussed in detail.

2. MODEL OF A POWER SYSTEM

For the improvement of dynamic stability of an interconnected power system, a single synchronous generator connected to an infinite bus (SMIB) system is taken into consideration. The synchronous generator connected to a bulk network of a transmission line can be represented as Thevenin's equivalent circuit with external impedance (R_e + jX_e) [1, 4-8]. Figure 1 shows the equivalent circuit of SMIB.

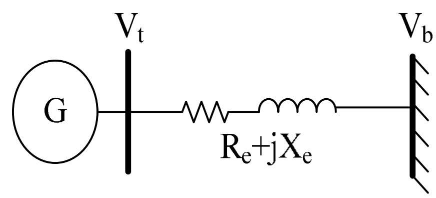

Figure 1: A single synchronous machine connected to an infinite bus (SMIB)

A simple linearized model of synchronous generator and excitation system is developed based on the linear model. The linearized equations for the synchronous machine are given by (the Δ subscripts are dropped for convenience) [1].

$$E'_{q\Delta} = \frac{K_3 E_{FD\Delta}}{1 + K_3 \tau'_{d0} s} - \frac{K_3 K_4 \delta_\Delta}{1 + K_3 \tau'_{d0} s} \quad (1)$$

$$T_{e\Delta} = K_1 \delta_\Delta + K_2 E'_{q\Delta} \quad (2)$$

$$V_{t\Delta} = K_5 \delta_\Delta + K_6 E'_{q\Delta} \quad (3)$$

$$\dot{E}'_q = -\left(\frac{1}{K_3 \tau'_{d0}}\right) E'_q - \left(\frac{K_4}{\tau'_{d0}}\right)\delta + \left(\frac{1}{\tau'_{d0}}\right) E_{FD} \quad (4)$$

From the torque equation we have

$$\dot{\omega} = \frac{T_m}{\tau_j} - \left(\frac{K_1}{\tau_j}\right)\delta - \left(\frac{K_2}{\tau_j}\right)E'_q - \left(\frac{D}{\tau_j}\right)\omega \quad (5)$$

By the definition of ω_Δ

$$\dot{\delta} = \omega$$

The complete state-space model of the synchronous generator with excitation system is given by

$$\begin{bmatrix} \dot{E}'_q \\ \dot{\omega} \\ \dot{\delta} \\ \dot{V}_1 \\ \dot{V}_3 \\ \dot{V}_R \\ \dot{E}_{FD} \end{bmatrix} = \begin{bmatrix} -\frac{1}{K_3\tau'_{d0}} & 0 & -\frac{K_4}{\tau'_{d0}} & 0 & 0 & 0 & \frac{1}{\tau'_{d0}} \\ -\frac{K_2}{\tau_j} & 0 & -\frac{K_1}{\tau_j} & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \frac{K_6K_R}{\tau_R} & 0 & \frac{K_5K_R}{\tau_R} & -\frac{1}{\tau_R} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau_F} & \frac{K_F}{\tau_F\tau_E} & -\frac{K_F(S'_E+K_E)}{\tau_F\tau_E} \\ 0 & 0 & 0 & -\frac{K_A}{\tau_A} & -\frac{K_A}{\tau_A} & -\frac{1}{\tau_A} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{\tau_E} & -\frac{(S'_E+K_E)}{\tau_E} \end{bmatrix} \begin{bmatrix} E'_q \\ \omega \\ \delta \\ V_1 \\ V_3 \\ V_R \\ E_{FD} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{T_m}{\tau_j} \\ 0 \\ 0 \\ 0 \\ \frac{K_A}{\tau_A}V_{REF} \\ 0 \end{bmatrix}$$

The state space model is represented with the excitation system only with state variables given by [1]

$$x^t = \begin{bmatrix} E'_q & \omega & \delta & V_1 & V_3 & V_R & E_{FD} \end{bmatrix} \quad (6)$$

The V_{REF} and T_m are the driving functions by assuming that V_S is zero [1].

3. ARTIFICIAL NEURAL NETWORKS (ANNs)

An artificial neural network (ANN) is a computational structure that is inspired by a crude electronic model based on biological nervous system in the brain. A neuron can be compared to the human brain in two ways. First, the network gets the information from its surroundings through a training process. Second, the neural network stores the acquired information within inter-neuron connection strengths or synaptic weights [4-5], [7-8], [26].

A learning rule, also referred as a training algorithm of a neural network, is used for adapting the weights and biases of a neural network and for training the network to perform a particular task. The learning mechanism adapts the weights of the different architectures and hence leads to a modification in the strength of interconnection. The selection of type of learning depends upon the behavior in which the parameter changes take place. There are two broad categories of learning rules in a neural network i.e., supervised learning and unsupervised learning [7-8], [26-28].

3.1 MULTILAYER PERCEPTRON NEURAL NETWORK (MLPNN)

Multilayer feedforward network is a particular type of neural networks. It consists of a set of source nodes which forms the input layer, one or more hidden layers, and one output layer. The input signal is applied in a forward direction through the network, on a layer-by-layer basis as shown in figure 2.

Multilayer perceptron networks are applied successfully for solving some difficult and complex problems by training them in a supervised learning scheme with a highly popular back-propagation algorithm. The back-propagation algorithm is based on the error-correction learning rule [4-5], [7-8], [26-28].

A multilayer perceptron network contains one input layer, one or more hidden layers and one output layer. The input layer consists of input data of the network. The hidden layer consists of computational nodes known as hidden neurons. The hidden neurons perform function of the interaction between the external input and network output in an efficient manner and extraction of higher order statistics. The function of the source nodes, in input layer of network, is to supply the input signal to neurons in the second layer (1st hidden layer). The 2nd layer's output signals are applied as inputs to the third layer and so on. The set of output signals constitutes the overall response of network to the activation pattern supplied by source nodes in the input first layer [7-8], [26-28].

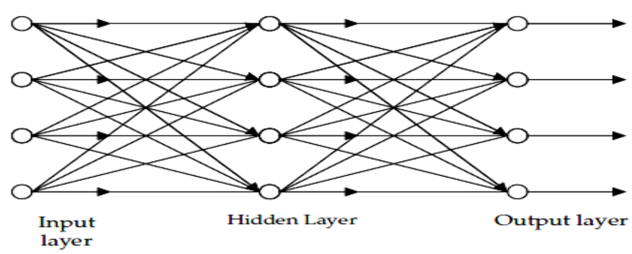

Figure 2: A multilayer feedforward neural network (MLPNN)

The back-propagation learning algorithm is applied for training multilayer perceptron (MLP) networks which is based on supervised learning. The algorithm is applied for adapting weights and biases of the neural network and reducing the error in its predictions on the training set [7-8], [26-28].

3.1.1 Levenberg-Marquardt Backpropagation

Levenberg-Marquardt is the fastest version of back-propagation algorithm. It is highly recommended as a favourite supervised algorithm, although it needs more memory than other algorithms [7-8]. The algorithm has been developed to approach second-order training speed without solving the Hessian matrix. For training feedforward networks the performance function takes the form of a sum of squares, therefore the Hessian matrix has been approximated as:

$$H = J^T J \quad (7)$$

The gradient can be solved as

$$g = J^T e \tag{8}$$

Where J refers to a Jacobian matrix consisting of first derivatives of the network errors with respect to the weights and biases, and e represents network vector errors. The Jacobian matrix can be easily solved through a standard BP technique which is simpler than the Hessian matrix.

The algorithm applies this approximation to the Hessian matrix as:

$$X_{j+1} = X_j - \left[J^I J + \mu I\right]^{-1} J^I e \tag{9}$$

This algorithm is the fastest scheme for learning moderate-sized multilayer perceptron neural networks. There is an efficient application of the algorithm in MATLAB software; because the evaluation of the matrix equation in MATLAB is a built-in function therefore its attributes become even more pronounced.

4. MODEL OF SYNCHRONOUS MACHINE WITH MLP FFNN BASED PSS

The complete linearized model of synchronous generator with AVR and feedforward neural network based PSS is shown in figure 3 with their parameters. The input to the proposed power system stabilizer is speed/frequency and output is applied at the summing junction of the reference voltage [1, 6].

The methodology and results are discussed in detail to investigate the performance of a single machine infinite bus using MLP feedforward neural network PSS and comparing with conventional power system stabilizers.

A multilayer perceptron FFNN has been trained with the Levenberg-Marquardt back-propagation (BP) learning algorithm which is based on the supervised learning of artificial neural networks. The Levenberg-Marquardt BP is used because it is faster than the ordinary BP algorithm [7-8]. In this work, the network is trained to behave as a special type of a conventional controller. Inputs and target data for training of neural network are created from the input and the output of that controller in a closed loop fashion in conjunction with the plant.

Proposed MLP power system stabilizer is developed considering PID controller as input for the network during the training process. Neural network controller created in this way will have unique arrangement, which will remain constant once the training process is completed. The resulting controller includes more predictable characteristics which can be found in various types of self-adaptive control systems.

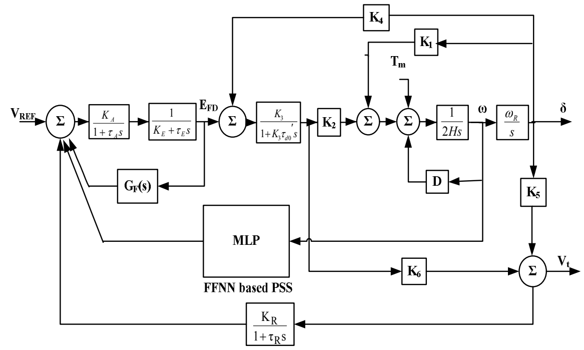

Figure 3: Linear model of synchronous machine with MLP FFNN based PSS

The selection of a suitable network structure is crucial for a particular application. A single hidden layer MLP network constitutes a universal approximation property. The network learns faster if hyperbolic tangent transfer function is used as the nonlinear activation function of hidden layer neurons. The number of hidden layer neurons is to be found by some trial and error procedure. Since the approach is based on the supervised learning of neural networks, hence the data for training (inputs and the target of the network) must be available. For this purpose, we recorded three inputs at the PID incoming signal and one output signal outgoing form PID. Figure 4 shows the MLP network for the model.

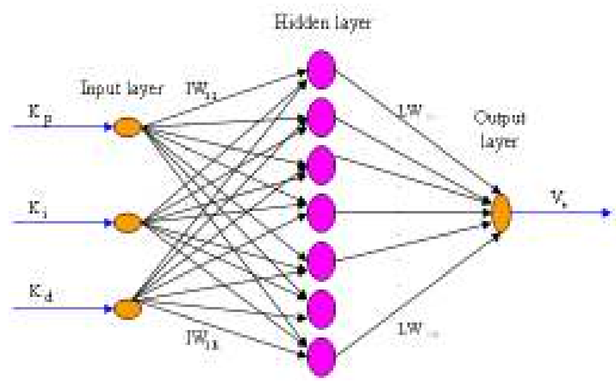

Figure 4: Multilayer perceptron network for PID power system stabilization

The three inputs of PID controller gain are applied as inputs to the input layer of the multilayer perceptron neural network. Terminal voltage and speed are the two required outputs of the proposed system.

A feedforward multilayer perceptron neural network has two layers. The first layer is a hidden layer which has weights coming from the input. It uses tangent sigmoid (tansig) transfer function. The second layer is the network output. The weights and biases are initialized and adapted with a specified learning scheme. The network is trained with specified hyperbolic tangent sigmoid transfer function. The performance of the network is measured according to the predetermined performance function. The learning parameters are as: Show = 5, i.e., after every 5^{th} iteration the result is shown, Learning rate = 0.05, Epochs = 10000, it is the maximum number of iterations, Goal = 1e-6. For training of MLP network Levenberg-Marquardt BP supervised learning algorithm has been applied. This is the faster than the ordinary back-propagation algorithm.

5. SIMULATION RESULTS

5.1 At normal loading conditions

Transient responses of terminal voltages (V_t):
The transient responses of terminal voltages are shown below with normal loading conditions (P= 1.0 pu and Q= 0.62 pu). The simulation result of terminal voltage shows the transient responses with conventional and proposed PSS in figure 5. The settling and rise time characteristics show the improvement in transient responses with better applicability, suitability, simplicity, and efficiency of

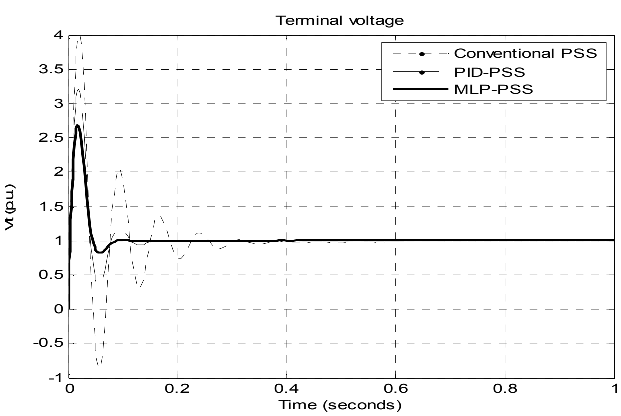

Figure 5: Combined responses of terminal voltage with conventional, PID and MLP-PSS

MLP-PSS over all other power system stabilizers.

Dynamic performance of frequency deviation (Δω):
The performance of the proposed MLP power system stabilizer in case of dynamic response of speed/frequency deviation is investigated at loading conditions (P= 1.0 pu and Q= 0.62 pu) as shown in figure 6.

At normal loading conditions figure 6 shows the better settling and rise time characteristics of proposed PSS which improves dynamic responses with better performance in frequency deviation over all other conventional PSS.

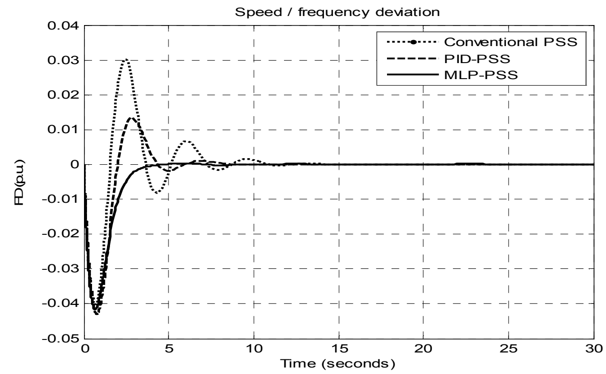

Figure 6: Combined response of frequency deviation with Conventional, PID and proposed MLP PSS

5.2 At 10% increase in loading conditions

Now the performance of the multilayer perceptron PSS is investigated by increasing a 10% load on the synchronous generator.

Transient responses of terminal voltages (V_t) at 10% increase

In figure 7, the terminal voltage response is investigated at 10% increase in step change after 0.4 seconds with conventional and proposed PSS.

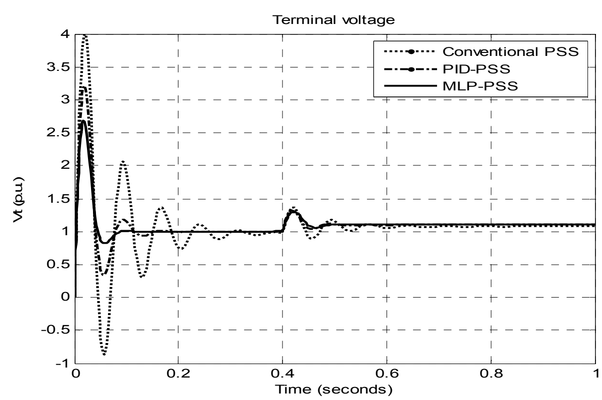

Figure 7: Combined response of terminal voltage with Conventional, PID and proposed MLP PSS at 10% change in load.

Dynamic performance of frequency deviation (Δω) at 10% increase:
Figure 8 shows that the dynamic responses of frequency deviations of all PSS at 10% increase in loading conditions after 0.4 seconds. Figure 7 and 8 compare the responses of a conventional and MLP PSS at 10% loading change and prove that the MLP is better for transient and dynamic responses.

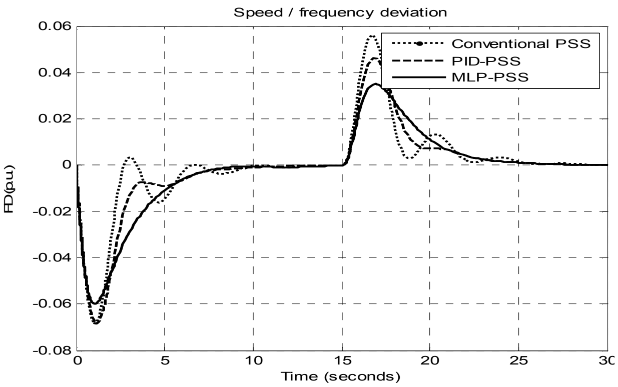

Figure 8: Combined responses of frequency deviation with Conventional, PID and MLP-PSS at 10% change in load.

6. CONCLUSIONS

In power system networks, low frequency oscillations have become a major concern for many years. In order to depress low frequency oscillation, the power system stabilizer parameters must be adjusted when there are changes in power network conditions.

This work proposes the suitable applicability of multilayer perceptron feedforward neural network power system stabilizer as controller to tune the power system stabilizer parameters for achieving better enhancement in stability. MLPFFNN PSS is developed with the help of PID-PSS in parallel and compared the responses with the performances of transient and dynamic responses at normal and 10% changing in operation conditions. For training MLP neural network, real power and reactive power of synchronous machine are chosen as the input signals and the output are; the desired power network stabilizer parameters.

The simulation results with comparisons of rise time, settling time and overshoot indicate that the FFNN-PSS control system ensures improved performances in transient response of terminal voltages and dynamic stability in case of angular speed/frequency at normal as well as at changing operating conditions.

The particular conclusions concerned the MLP architectures:

- MLP networks architectures construct seven neurons in input (hidden) layer and its activation transfer function is hyperbolic tangent sigmoid. Only one neuron in output layer is created and its linear activation transfer function is ample for reasonable presentation.
- Popular back propagation with Levenberg-Marquardt algorithm is utilized for the upgrading in the training time.
- It is observed in this work, that a small number of hidden layer neurons are desirable for the development of MLP networks for the designing of power system stabilization system of electrical power system. .

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