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Selection of Suitable Feedforward Neural Network (FFNN) Based Power System Stabilizer (PSS) For Excitation Control of Synchronous Generator

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ABSTRACT

Low frequency oscillation problems in electrical power system have become a major concern for many years. In order to depress low frequency oscillation, the power system stabilizer (PSS) parameters must be tuned when there are changes in loading conditions. For this purpose an artificial (AI) feedforward neural network (FFNN) based PSS with single machine connected to infinite bus (SMIB) system is proposed for tuning the PSS parameters.
The conventional PSS is simulated in MATLAB to control the oscillations of synchronous machine at different loading conditions. The data of speed deviation and terminal voltage responses are generated and stored as the input for FFNN based PSS for training purposes. The FFNN architectures of multilayer perceptron (MLP) with back propagation (BP) and radial basis function (RBF) with orthogonal least square (OLS) algorithms are utilized to design the MLP-RBF NN based PSS controller, in order to improve the stability of synchronous machine.
The performance of the proposed FFNN based PSS (Both MLP & RBF architectures) is compared with and without conventional power system stabilizer. Simulation result indicates that the FFNN based stabilization is more adaptive and flexible than the conventional stabilizer. It is also found that the proposed controller can enhance both the transient stability and dynamic performance of the system with promising results over wide range of operating conditions and disturbances.
KEYWORDS: Synchronous machine, Power system stabilizer, Multilayer perceptron, Radial basis function, Matlab/Simulink

INTRODUCTION

The excitation system of the synchronous generator with automatic voltage regulator (AVR) controls the generated electromotive force or EMF and therefore maintains not only the reactive power (Q) flow but the power factor and current magnitude as well. The governor together with load frequency control regulates the frequency of the generator and maintains the real power (P) [1-3].

The main purpose of the power system control is to produce and deliver electrical energy to utility as economical and reliable as possible while maintaining the generated EMF and frequency of the synchronous machine within specified limits. Therefore the control of active power and reactive power is very important to maintain the system in steady state condition [3-8].

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 deviates the rotor angle of the generator. 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 [1-2, 6]. The unwanted impact of these regulators can be compensated by introducing additional signals in the feedback loop. These additional signals are mostly taken from angular speed by inserting an additional stabilizing signal into the reference voltage summing junction of the excitation system. The networks used to compensate these unwanted signals caused by modern regulators are called "power system stabilizer (PSS)" networks [1]. The function of the PSS is to detect an oscillation and to generate an additional signal used to provide positive damping to the AVR loop of generation unit. The mostly used existing PSS focused in literature is known as lead-lag network [6], consists of three stages namely a phase compensation stage, a signal

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washout stage and a gain block stage. It must produce electrical torque component on the rotor in phase with speed deviations for compensating the rotor damping or oscillation. The input signal of PSS may be any one of the generator speed, frequency or electrical power. For a given input signal, the parameters of PSS must compensate the gain and phase characteristics of the excitation system of the synchronous generator [1-2, 6]. The parameter gain settings of the conventional PSS are mostly constant and are determined at fixed particular operating or loading conditions. The performance of these PSS is better for those particular working conditions, but in case of variable loading conditions their response is poor [9-11].

LITERATURE REVIEW ON PSS

In literature a considerable efforts are taken on the application of power system stabilizer to enhance the stability of the electrical power system (EPS).

Conventional PSS

Heffron and Phillips 1952 [12] were the pioneer of representing the small disturbance model with linearized parameters of a single synchronous machine connected to an infinite bus (SMIB) system. They investigated that the large turbo-generators under excited operation are affected due to modern amplidyne voltage regulators. The application of modern voltage regulators for excitation system much affects the dynamic stability of turbo-generators in the under-excited region.

De Mello et al 1969 [2] explored the small scale stability characteristics of a SMIB through external impedance by means of frequency response analyses showing effects of machine and system parameters, AVR gain and stabilizing functions. P. Kundur in 1999 [6] discussed the stability criterion with respect to synchronous equilibrium and introduced the mathematical expressions for the dynamic stability as a set of linear time invariant differential equations. Chan and Hsu in 1983 [9] presented an optimal variable structure power system stabilizer for improving the dynamic stability of the synchronous machine by providing the damping torque component to the generator.

Gupta et al in 1985 [10] proposed a criterion for designing a PSS, to cancel the negative damping torque produced in a synchronous machine and AVR.

Yuan and Chang (1986) [13] investigated digital and analog stabilization of power system using a proportional-integral (PI) PSS by the root-locus method for obtaining the optimal stabilizer gains of the PI stabilizer.

Hsu and Liou (1987) [14] proposed a self-tuning proportional-integral-derivative (PID) PSS for improving the dynamic stability of a single synchronous generator over a wide range of loading conditions. They proposed that the self-tuning PID-PSS can enhance both the transient stability and the dynamic stability of the generator.

Wu and Hsu (1988) [15] proposed a self-tuning PID-PSS for multi-machine system.

Artificial intelligent (AI) techniques based PSS

Recently researchers are concerned with artificial intelligence techniques as an effective tool to resolve many power system stability problems and to develop an efficient PSS that could be more effective when properly joined together with conventional mathematical approaches. These techniques include artificial neural network (ANN), Fuzzy logic, and intelligent optimization and hybrid artificial intelligent techniques by Lokman 2009 [16].

Artificial neural network (ANN) based PSS:

Hsu Y. Y (1991) [17]investigated tuning of proportional integral (PI) type PSS using an artificial neural network (ANN) by taking active power (P) and power factor (PF), as the input signals to the ANN. They proposed that the ANN based PSS provides good damping over a wide range of loading conditions. Zhang et al (1993) [18] proposed an ANN based Adaptive PSS. Liu et al (2003) [19] designed an indirect adaptive neural network based PSS (INDC) consisting of a neuro-controller and a neuro-identifier.

Fuzzy logic (FL) based PSS:

Majid et al I 2002 [20] replaced a PSS with a fuzzy logic controller in which frequency deviation and acceleration of synchronous generator rotor were taken as input signals to the controllers. Hariri and Malik (1996) [21] proposed a fuzzy logic based PSS with learning ability that combines the advantages of both nueral network and fuzzy logic control schemes. Nallathambi and Neelakantan in 2004 [22] proposed fuzzy logic based PSS for increasing stability of two area.

Optimization based intelligent techniques:

Various intelligent optimization methods are applied for searching optimal or sub-optimal solution of power system stability problems. These techniques include genetic algorithm (GA), particle swarm optimization (PSO), Tabu search (TS) etc. Abido (1999) [23] proposed the Tabu search algorithm for SMIB and multi-machine power systems for various loading conditions to find optimal parameters of conventional lead-lag PSS.

Al-Hinai in 2009 [24] proposed the particle swarm optimization based PSS for self tuning of parameters of PSS. Haddin et al (2011) [25] proposed PSO based coordination of AVR-PSS and AGC for improving the dynamic stability of the generator. Hemmati et al in 2011 [26] proposed PID-PSS based hybrid genetic algorithm for SMIB.

Hybrid artificial intelligent techniques:

Two or more artificial intelligent techniques applied simultaneously in series or in integration to obtain successful results are known as hybrid AI techniques. Djukanovic et al in 1997 [27] presented adaptive fuzzy logic controller based on unsupervised learning neural nets for increasing the transient stability of a hydropower system. To avoid these drawbacks, Abido and Abdel-Magid 1999 in [28] proposed a fuzzy basis function network (FBFN) to develop PSS where, the strengths of both fuzzy logic and neural networks were combined by emerging the learning abilities of ANN to fuzzy logic systems. Afzalian and Likens in 2000 [29] applied GA on SMIB.

PROBLEM STATEMENT

The power system stabilizers mostly discussed in literature are useful for fixed working conditions. The gain settings of these PSS are obtained at specified operating conditions and hence there is a challenge for light, medium and heavy loading conditions. These gain settings are useful for those operating conditions at which they are designed. The problem of instability may be created if these loading conditions change from one value to another as discussed by Malik in 2002 [30].

Electrical power system is highly nonlinear and complex which includes many aspects of circuits, phasors, complex algebra, laws and other mathematical approaches. The researcher who works in this field must have vast knowledge of this field, which is very difficult.

The demand of power system stability is increasing along with the popularity of electrical products. An AVR is used to maintain changes in the output voltage, avoiding the malfunction of the electrical load terminals. Many synchronous machines are manufactured with high gain, fast acting voltage regulators for increasing the dynamic stability to keep the generator in synchronism with the interconnected power system during sudden disturbances. The high gain and fast action of excitation system produces the negative damping torque to the rotor of the generator. Therefore a controller referred as power system stabilizer is needed to be connected with synchronous generator to compensate the negative effect of fast action and high gain of AVR and other sources of negative damping.

SUGGESTED SOLUTIONS

From this detailed discussions, a power system stabilizer is required, which should possess self-learning and adaptation properties of handling the changes and uncertainties in the system. Hence 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.

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 Suykens 1996 [31].

The easily modeling of complex system is the superiority of neural networks to conventional controller system; they require a precise information and knowledge with mathematical models. Sometimes this information and knowledge is missing for conventional controllers; hence the problem becomes more crucial. The NN does not require such conditions and can handle such complex systems very relatively easier. They require input-output mapping relationships and their data to learn. They can learn and train during on line and off line situation of the process of system (Fausett 1994 [32] and Tanaka 1996 [33]). They do not require mathematical modeling, computer programming and deeply understanding of the system. They are naturally generalized and parallel distributed in their architecture structures.

Feedforward neural network based PSS is proposed in this research work. Both types of FFNN known as "radial basis function" (RBF) network with orthogonal least square (OLS) learning algorithm and "multilayer perceptron" (MLP) network with back propagation (BP) algorithms are developed. 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.

OBJECTIVES OF WORK

In this research work feedforward neural network based power system stabilizer for the improvement of power system stability is suggested. To follow these ideas, the following objectives are focused:

- To study the power system fundamentals, stability and its importance in power system control designing.
- To study the concept of power system control, the importance of controlling active and reactive powers with the changing behaviour of voltage and frequency.

- To study the mathematical modeling of synchronous generator with linearized equations in state space and transfer function formation.
- To develop the SMIB simulation model of synchronous machine including AVR excitation system, LFC and PSS using Matlab/Simulink techniques along with their numerical values.
- To focus on the introduction of ANN, its architectures, algorithms, learning, training and design methodology.
- To study neural network toolbox of Matlab, its methods of training and designing the proposed RBF/MLP power system stabilizers.
- To compare the results of conventional PSS, PID PSS and RBF & MLP PSS with conclusions and future suggestions.

MODEL OF A POWER SYSTEM

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

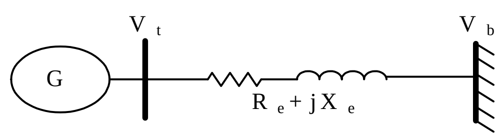

Figure 1: A single synchronous machine connected to an infinite bus (SMIB)

The 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) [1-8].

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

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

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

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

From the torque equation we have

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

By the definition of ω_Δ

$\dot{\delta} = \omega$

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

$$\begin{bmatrix} \dot{E}'_q \\ \dot{\omega} \\ \dot{\delta} \\ \dot{V}_1 \\ \dot{V}_3 \\ \dot{V}_R \\ \dot{E}_{FD} \end{bmatrix} = \begin{bmatrix} -\frac{1}{K_3 \tau'_{d0}} & 0 & -\frac{K_4}{\tau'_{d0}} & 0 & 0 & 0 & \frac{1}{\tau'_{d0}} \\ -\frac{K_2}{\tau_j} & 0 & -\frac{K_1}{\tau_J} & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \frac{K_6 K_R}{\tau_R} & 0 & \frac{K_5 K_R}{\tau_R} & -\frac{1}{\tau_R} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau_F} & \frac{K_F}{\tau_F \tau_E} & -\frac{K_F (S'_E + K_E)}{\tau_F \tau_E} \\ 0 & 0 & 0 & -\frac{K_A}{\tau_A} & -\frac{K_A}{\tau_A} & -\frac{1}{\tau_A} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{\tau_E} & -\frac{(S'_E + K_E)}{\tau_E} \end{bmatrix} \begin{bmatrix} E'_q \\ \omega \\ \delta \\ V_1 \\ V_3 \\ V_R \\ E_{FD} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{T_m}{\tau_j} \\ 0 \\ 0 \\ 0 \\ \frac{K_A}{\tau_A} V_{REF} \\ 0 \end{bmatrix}$$

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

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

The V_{REF} and T_m are the driving functions by assuming that V_S is zero [1-8].

POWER SYSTEM STABILIZER

A high gain, fast acting voltage regulator introduces a damping torque component proportional to K_5. Also under heavy loading conditions K_5 can be negative. In these conditions dynamic stability is of concern because the excitation system introduces low system frequency oscillations. Therefore voltage regulator is often assumed to introduce negative damping. To compensate the damping and to improve the system dynamic stability in general, artificial signals for generating damping torque in phase with the angular frequency are produced which are known as "supplementary stabilizing signals". The equipment used to provide these stabilizing signals are called "power system stabilizers" networks by Anderson 2007 [1].

Signals of power system stabilizer are injected in excitation systems at the summing point where terminal voltage and reference voltage are added for obtaining the error fed to the AVR controller. The stabilizing signal V_s usually obtained from speed or frequency deviation is processed through a suitable network to obtain the desired phase relationship. Such an arrangement is shown schematically in Figure 2. [1].

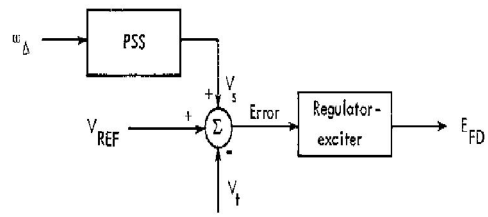

Figure 2: Schematic diagram of power system stabilizer

The PSS is shown here as a feedback element from the shaft speed and is given in the form

$$Gs(s) = \frac{K_0 \tau_0 s}{1+\tau_0 s}\left[\frac{(1+\tau_1 s)(1+\tau_2 s)}{(1+\tau_2 s)(1+\tau_3 s)}\right] \tag{7}$$

The first term in Eq. (7) consists of a reset term used to washout the compensation effect after a time lag τ_0, with typical values of 4sec to 20 or 30 sec [Anderson 2007]. The reset control will assure no permanent deviation in the terminal voltage for a prolonged error in a frequency, such as might be in an overload condition.

The second component in Eq. (7) is a lead compensation pair used to improve the phase lag through the network from V_{REF} to $\Delta\omega$ at the power system frequency of oscillation.

The PSS produces positive component of damping torque that is in phase with the frequency deviation and used to compensate negative damping in rotor. This component needs a phase-lead circuit for compensating the phase-lag between exciter input and the resulting electrical torque. The phase characteristics of the power system stabilizer depend upon the system parameters and the loading condition. The required phase-lead at any loading condition can be obtained by choosing the suitable values of τ_1, τ_2 τ_3 and τ_4 time constants.
A high-pass filter is used in the signal washout component which is used to block steady state changes in the angular frequency from changing the field exciter voltage [1, 6].

MODEL AND DESIGN METHODOLOGY OF FFNN

Model of Power System Controller

The complete linearized model of synchronous generator with AVR and feedforward neural network based PSS is shown in Figure 3 with the following parameters and numerical values. The input to the proposed power system stabilizer is speed/frequency and output is applied at the summing junction of the reference voltage.

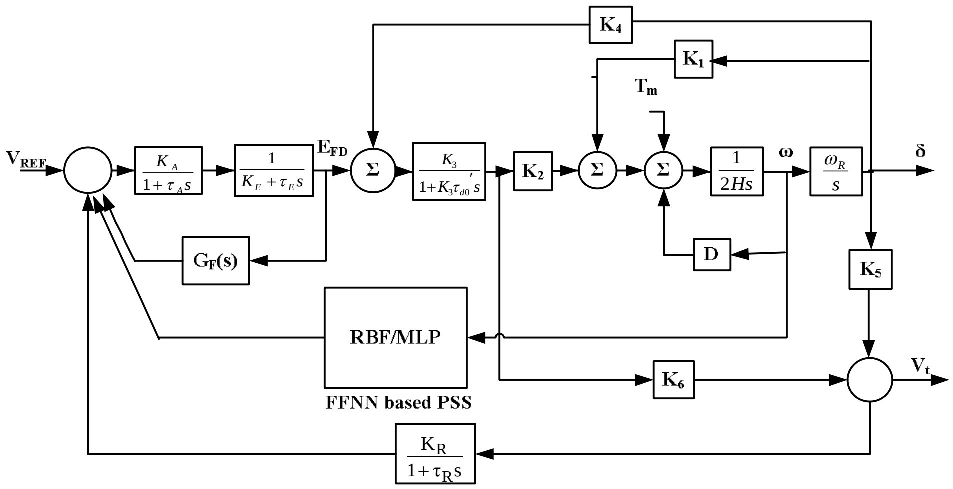

Figure 3: Linear model of synchronous machine with FFNN based PSS

Numerical Values of Operating Conditions

The following operating conditions are obtained [1] for a synchronous machine connected to an infinite bus through a transmission line with external resistance $R_{e,}$ 0.02 pu and inductance L_e 0.4 pu.

The active power $P = 1.0$ pu
Reactive power $Q = 0.62$ pu
Power factor of the load p.f = 0.85 pu.
Terminal voltage $V_t = 1.0$ pu
Infinite bus voltage $V_b = 0.828$ pu
Angular frequency $\omega_R = 377$ rad/sec
Dapming constant $D = 0.8$
Inertia constant $H = 10$
Reference voltage $V_{ref} = 1$
Voltage load change $\Delta V_L = 0.05$
Amplifier gain $K_A = 400$
Exciter gain $K_E = 200$
Sensor gain $K_R = 1$
Exciter time constant $\tau_E = 0.05$
Sensor time constant $\tau_R = 0.05$
Amplifier time constant $\tau_A = 0.5$

Linear parameters of synchronous generator

$K_1 = 1.0755$
$K_2 = 1.2578$
$K_3 = 0.3072$
$K_4 = 1.7124$
$K_5 = -0.0409$
$K_6 = 0.4971$

The PSS parameters

Wash-out network $K_s = 120\tau_0 = 1$
Lead-lag network $\tau_1 = 0.024$, $\tau_2 = 0:002$
Lag-lead network $\tau_3 = 0:024$, $\tau_4 = 0:24$

PID controller Parameters

Proportional gain $K_p = 1$
Integral gain $K_i = 2$
Derivative gain $K_d = 0.5$

In this work the performance of a single machine infinite bus has been studied by using both types of feedforward neural network applied to a conventional power system stabilizer. The methodology and results for both types are described in detail.

DESIGN OF MULTILAYER PERCEPTRON NETWORK

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 [Foda 2002]. 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.

At the above discussed working conditions of the model for the applications of FFNN, model is simulated and PID controller is used as a trainer for the network in the training process. The resulting network has learnt to behave in the same style as its trainer i.e. it will perform well at that specific working condition. A neural network controller created in this way will have an arrangement, which will remain constant once the training process is finished. The resulting controller includes more predictable characteristics which are found in various types of self-adaptive control systems.

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.

In this study a multilayer perceptron network has been created which gives satisfactory performance at various loading conditions. 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.

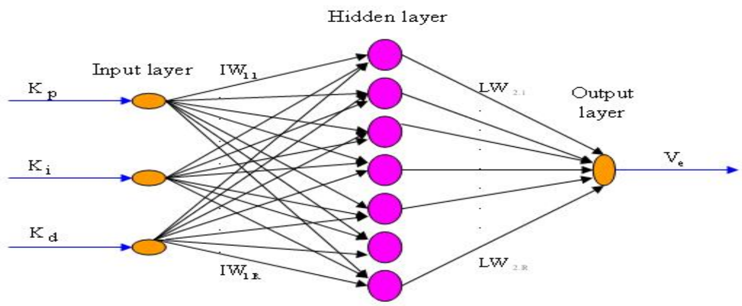

Figure 4: Multilayer perceptron network for PID power system stabilization

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.

DEVELOPMENT OF MLP NETWORK

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 steps for training the PID model are discussed below**:**

1. Network architecture

The multilayer perceptron feedforward neural network architectures have been selected.

2. Range of the input and initialization of the network parameters

In the second step the ranges of the PID incoming signal and output signal outgoing from PID are recorded.

3. Structure of the network

Only one hidden layer network is chosen for structure of the network,

4. Numbers of neurons in the hidden layer

Seven (07) nodes or neurons are chosen in the hidden layer.

5. Numbers of neurons in the output layer

For second or output layer one (01) neuron is selected

6. Activation function in the layers

A hyperbolic tangent sigmoid (tansig) transfer function is selected for the hidden layer and linear (purelin) transfer functions are selected for the output layer as the activation function.

7. Basic learning scheme

The basic learning scheme applied for training of the network is back-propagation algorithm.

8. **Learning parameters:** Following are the learning parameters:

i) Show = 5, i.e., after every 5th iteration the result is shown

ii) Learning rate = 0.05

iii) Epochs = 10000, it is the maximum number of iterations

iv) Goal = 1e-6

9. Training of the network

For training of MLP network Levenberg-Marquardt BP supervised learning algorithm has been applied. This is the faster than the ordinary back-propagation algorithm.

10. Performance function

The mean squared error (mse) function is selected as the performance function.

PERFORMANCE WITH MULTILAYER PERCEPTRON NETWORK

Figures 5 to 8 demonstrate the performances of terminal voltage and angular speed or frequency deviation responses of proposed MLP-PSS with CPSS, and PID-PSS.

At normal loading conditions: (*Transient responses of terminal voltages V_t)*

The transient responses of terminal voltages are shown below with the normal loading conditions (P= 1.0 pu and Q= 0.62 pu) as mentioned above.

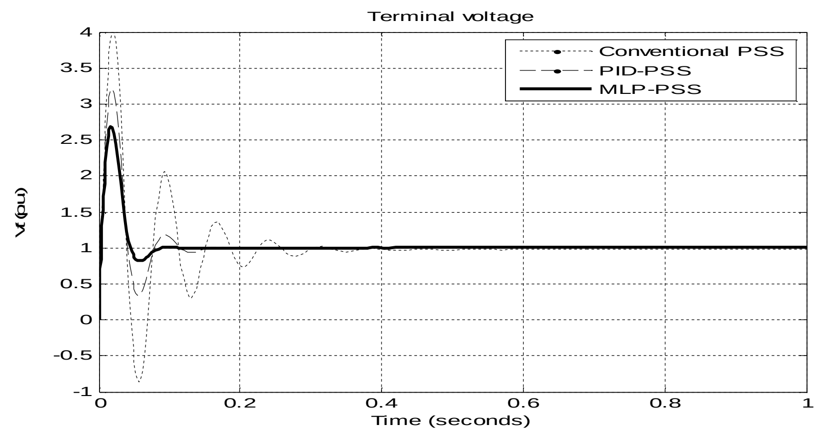

Figure 5: Responses of terminal voltage with conventional, PID and MLP-PSS

The simulation results of transient responses of terminal voltage shown in Figure 5 demonstrate the simplicity, applicability and efficiency of MLP-PSS over all other power system stabilizers. It is also observed that the under these normal loading conditions the responses of a multilayer perceptron neural network is much better from settling and rise time characteristics.

Dynamic performance of speed/frequency deviation

The performance of the proposed MLP power system stabilizer for speed/frequency deviation is investigated at normal loading conditions (P= 1.0 pu and Q= 0.62 pu).

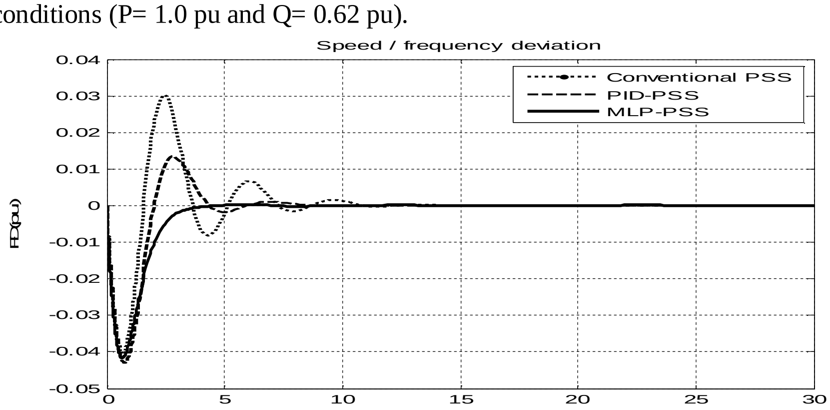

Figure 6: Response of frequency deviation with Conventional, PID and proposed MLP PSS

At normal loading conditions (P= 1.0 pu and Q= 0.62 pu), the dynamic responses of speed/frequency deviations shown in Figure 6, prove the suitability and better performances of MLP-PSS when compared with other PSS.

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: The terminal voltage response is checked at 10% increase in step change after 0.4 seconds for all the types of PSSs.

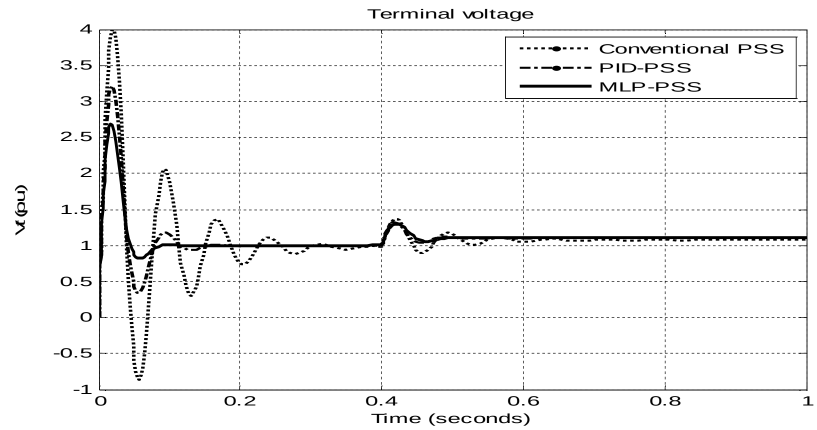

Figure 7: Response of terminal voltage with Conventional, PID and proposed MLP PSS 10% change in load

Dynamic performance of frequency deviation at 10% increase: Again, the response of the proposed MLP based PSS is compared with conventional and PID-PSS at 10% increase in the load

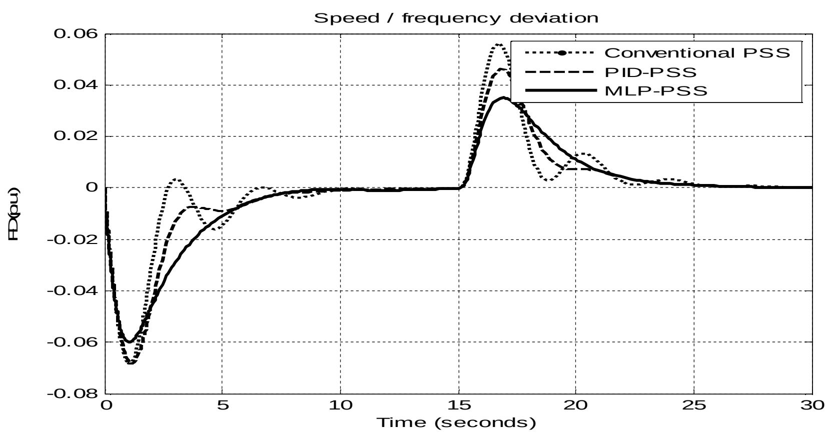

Figure 8: Responses of frequency deviation with Conventional, PID and MLP-PSS at 10% change in load.

METHODOLOGY OF DESIGNING RBF NETWORK

The RBF network is developed here for power system stabilization of synchronous generator. This type of neural network has several advantages over MLP network, such as:

As discussed earlier, there are no strict rules to select a particular number of neurons in the hidden layer of an MLP network for a specific application. On the other hand, in RBF networks the neurons in the hidden layer are created themselves. An orthogonal least squares (OLS) algorithm automatically chooses a suitable number of neurons in the hidden layer of a RBF network from a set of input data.

Although an MLP network has the universal approximation property but they do not possess the best approximation property. Whereas RBF networks are not only universal approximators but they also have the best approximation property. For a particular application RBF networks are mostly faster than MLP networks.

DESIGN OF RADIAL BASIS FUNCTION (RBF) NETWORK

A radial basis function network can be used to approximate a function. The neurons are added to the hidden layer until it meets the specified mean square error goal.

For the training of radial basis function network the following steps are revised until the network's mean square error falls below the goal.

- The network is simulated in MATLAB software.
- The input vector is found with the greatest error.
- A radial basis (radbas) transfer function neuron is added with weights equal to the vector of step 2.
- The linear (purelin) transfer function layer weights are redesigned to minimize error.
- It is found that twenty five (25) neurons are created in the hidden layer.
- One (01) neuron or node with linear transfer function is used in the output layer.
- Spread constant is 1.5
- Error goal is 0.00001.

PERFORMANCE WITH RADIAL BASIS FUNCTION NETWORK

The transient responses of terminal voltage and dynamic response of frequency deviation with conventional PSS, PID-PSS and RBF-PSS for synchronous generator are compared and discussed as shown in Fig. 4.9 to 4.12.

At normal loading conditions: (*Transient responses of terminal voltages Vt)*

The transient performance of the proposed power system stabilizer is compared with the CPSS, PID-PSS at normal loading conditions mentioned above in detail.

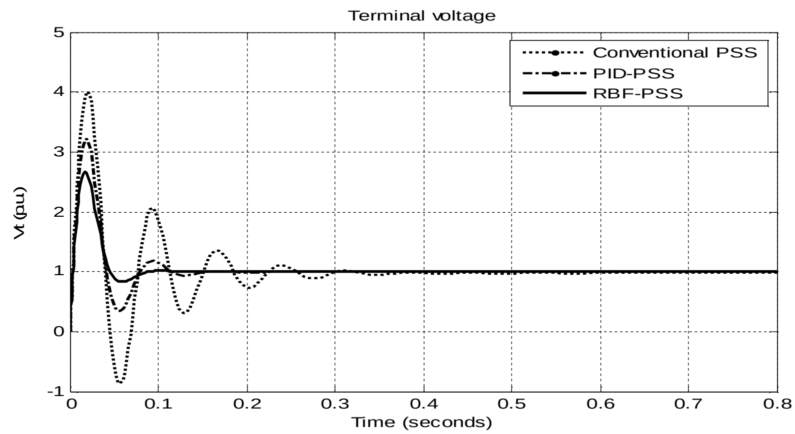

Figure 9: Response of terminal voltage with CPSS, PID and RBF-PSS

Dynamic performance of speed/frequency deviation:

The performance of the proposed RBF power system stabilizer for speed/frequency deviation is investigated at normal loading conditions (P= 1.0 pu and Q= 0.62 pu).

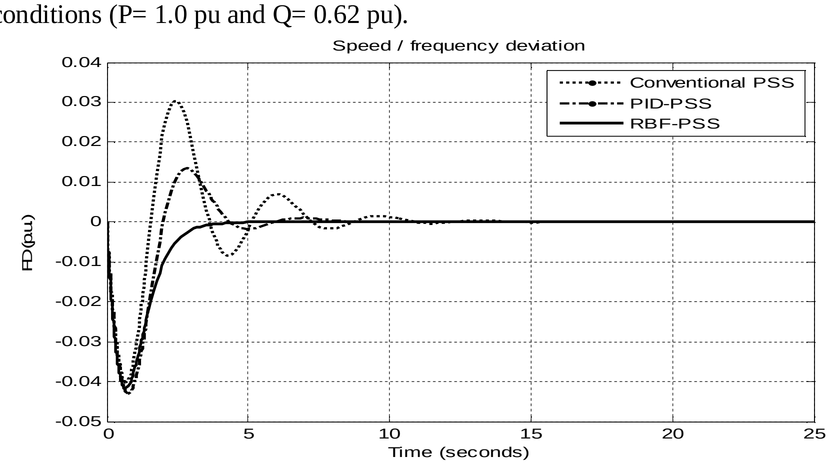

Figure 10: Response of frequency deviation with Conventional, PID and RBF PSS

At 10% increase in loading conditions: Now the performance of the radial basis function based PSS is investigated by increasing a 10% load on the synchronous generator.

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

The terminal voltage response is checked at 10% increase in step change after 0.4 seconds for all the types of power system stabilizers.

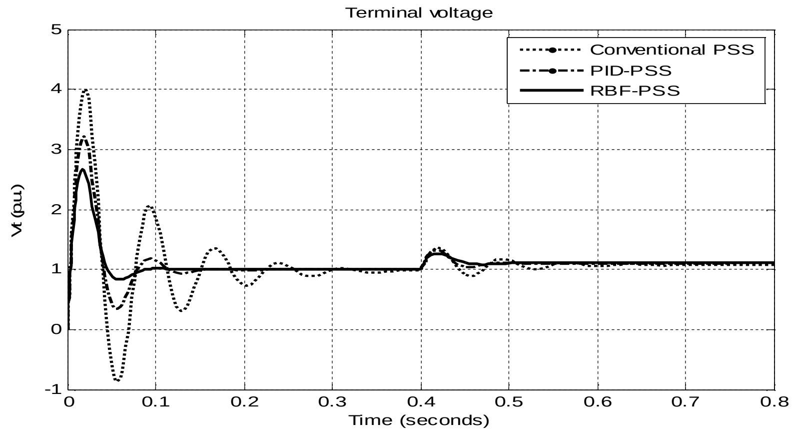

Figure 11: Response of terminal voltage with CPSS, PID and MLP PSS

Dynamic performance of frequency deviation at 10% increase

Again, the response of the proposed RBF based PSS is compared with conventional and PID-PSS after 10% increase in the load.

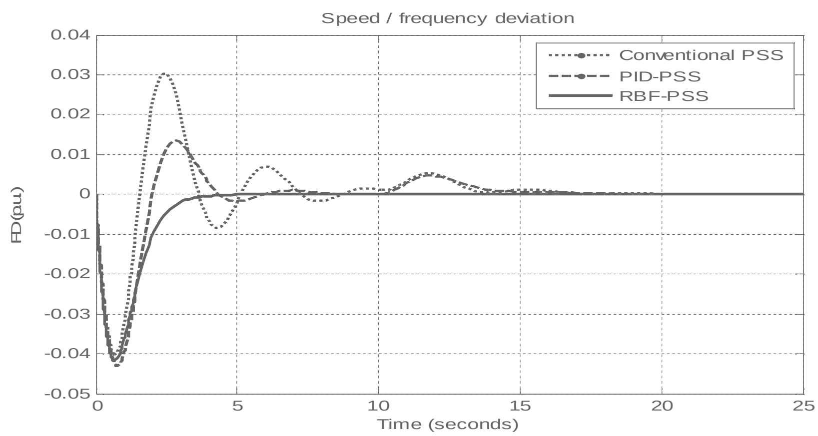

Figure 12: Response of frequency deviation with Conventional, PID and proposed RBF-PSS after 10% change in load

COMPARISON OF RESULTS

From a detailed discussion on the results obtained by both types of FFNN it is cleared that the performance of the RBF networks is better than the MLP networks. The RBF networks have favourable characteristics of the best approximation property and a compact network structure. The RBF networks have a faster training time than MLP networks. However, like in other applications RBF require more hidden layer neurons than MLP networks in this application for comparable performance levels. A comparison of the MLP and RBF networks is given in Table 1.

Table 1: Comparison of MLP and RBF networks

Type of Network	Time required for training	Number of neurons		Transfer function		SSE
		1st layer	2nd Layer	1st Layer	2nd Layer	
MLP	28 sec	07	01	tansig	pureline	1e-6
RBF	8 sec	25	01	radbas	pureline	1e-5

Comparisons of terminal voltage and frequency deviation for both types RBF and MLP networks in terms of the rise time, settling time and per unit overshoot of all the types of PSSs as shown in Tables 2-3.

Table 2: Frequency deviation comparisons

Type of PSS	Rise time (sec)	Settling time (sec)	Overshoot (p.u)
Conventional PSS	2.1	11	0.03
PID-PSS	2.4	07	0.014
MLPPSS	2.6	3.8	0.0
RBFPSS	**2.6**	**3.5**	**0.0**

Table 3: Terminal voltage comparisons

Type of PSS	Rise time (sec)	Settling time (sec)	Overshoot (p.u)
Conventional PSS	0.001	0.35	04
PID-PSS	0.001	0.18	3.25
MLPPSS	0.001	0.09	2.7
RBFPSS	0.001	0.08	2.75

CONCLUSIONS AND FUTURE IMPROVEMENTS

In this work a simulation program technique has been developed that can narrowly analysis the operation of complete model of synchronous machine with AVR excitation, LFC and PSS in the domain of transfer functions in order to determine the terminal voltage and speed/frequency responses of the model. With the help of this model, we have focused on PID-PSS system of synchronous generator in order to replace with feedforward neural networks (RBF & MLP) PSSs.

Hence a PID-PSS system is developed then trained in parallel with RBF & MLP and compared the responses at trained data at operating conditions described in section 3 in detail. We desire to design here a better controller for the power system stabilization system of synchronous generator in order to improve transient and dynamic stability of power system. This has been followed by some closing comments on the worth of this work.

CONCLUSIONS

The feedforward artificial neural network (FFANN) applications with promising performances in power system stability of synchronous generator excitation systems have been successfully implemented.

This work presents results concerning the use of feedforward neural networks to obtain a controller, which incorporates the properties of a conventional PID controller. Two types of feedforward neural networks, namely the multilayer perceptron (MLP) networks and radial basis function (RBF) networks have been proposed.

The simulation result indicates that the FFNN-PSS control system ensures superior responses at normal as well as changing operating conditions. Comparisons of rise time, settling time and overshoot of Tables 2-3 also specify the better performances of proposed technique.

FFNN controllers proffer improved performances in transient response of terminal voltages and good results of dynamic stability in case of angular speed/frequency.

Having above successful developments, the key termination which can be depicted from this work is that MLP and RBF architectures of FFNN are appropriate for this work. As they capitulate vigorous performance with the normal loading conditions at which they are trained and for other changing conditions of loading.

The particular conclusion concerned with the above architectures are outlined below

Multilayer perceptron (MLP) networks

- 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.
- The presentation of MLP network is vigorous within the ranges of operating condition which are considered in this work.
- A considerable shortcoming of MLP networks is that there is no clear-cut ruling for selecting a suitable number of hidden layer neurons for most favorable performance. This number is preferred by the assessment and error methods, preliminary with two or three neurons, and then growing the number regularly, in anticipation of acceptable performance is accomplished. This course of action is certainly, boring and time unbearable. 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.

Radial basis function (RBF) networks

Due to their distinguishing properties, simple network configuration, proficient learning process and finest estimations make the RBF networks most preferable in control applications. In this research work RBF networks are trained by means of the orthogonal least squares (OLS) algorithm. This technique of OLS algorithm chooses proper number of the radial basis function centres from input information; for this reason the dilemma of selecting the most favorable number of first or hidden layer neurons is involuntarily resolved. For this work, 25 neurons in the input layer with radial basis function as the activation function and one neuron with linear transfer function in the second or output layer are chosen for training.

Form the results it is obvious that the performance of radial basis function networks is as superior as can be accomplished and compared by the MLP networks. Furthermore, RBF networks take faster training time than MLP networks. RBF networks require more number of hidden layer neurons than MLP networks for the solution of the same problem at the same time.

The small variations in the responses are not reflected clearly due to sturdy network stuck between the synchronous generator and the infinite bus system.

The understanding and familiarity which have been achieve from beginning to end of this research and its implementation has been enormously priceless. The work implicated in the exploration and analysis of this thesis has broadened our scale towards power system control. There are many viewpoints in the research studies of the power system stability of synchronous generator in the field of electrical power system.

FUTURE IMPROVEMENTS

The simulation based research work with descriptions and results successfully develops and demonstrates an artificial neural networks based applicability and suitability for the control of excitation control system of synchronous machine to improve the stability of the system. Conversely, there are many features, which necessitate additional consideration. There are some areas in the simulation model that can be improved further on. With the intention of upgrading in the model, quite a few areas can be painstaking:

- Higher order model of turbine may be utilized instead of 1st order model.
- Nonlinearity performance between the input and output of the excitation system is practically observed which invites to implement the nonlinear model of excitation system.
- Actual load connection instead of simulation based load model is suggested to be connected to the terminal voltage.
- The model is connected to the infinite bus, hence the small changes in response are not observed because of strong grid.
- For this research work speed/frequency have been selected for the input of PSS, it is suggested that the rotor angle, and actual power or torque may be selected as the input of PSS.
- The on-line training of neural network controllers for this application will be another interesting and important development.

Hopefully in future, above recommendations will be implemented for a complete and more accurate simulation model.

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