APPLICABILITY AND SUITABILITY OF RADIAL BASIS FUNCTION NEURAL NETWORK IN EXCITATION CONTROL SYSTEM OF SYNCHRONOUS MACHINE

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ABSTRACT: *The supply of stable, reliable and economic electric energy is a major determinant of industrial progress and consequent rise in the standard of living the world over. The high gain and fast action of excitation system produces the negative damping torque to the rotor of the synchronous generator, which is handled with the introduction of power system stabilizer (PSS). The PSSs mostly discussed/proposed in literature are useful for specified fixed operating conditions. The varying load conditions are a challenge for stability of power system operation. The demand of power system stability is increasing along with the popularity of electrical products. Therefore, variant PSS is required, which should possess self-learning and adaptation properties of handling the changes and uncertainties in the system.*

To solve this problem radial basis function neural network (RBFNN) based PSS with single machine connected at infinite bus (SMIB) model is proposed by taking angular frequency as an input to improve the transient and dynamic stability of electrical power system at varying loads.

The simulations results using Matlab/Simulink and neural network toolbox are compared with conventional and proposed RBFNN PSS at varying load conditions. The applicability and suitability of the proposed PSS show the improvements in transient and dynamic state stability enhancement.

Keywords**:** Power system stability, Synchronous machine, Power system stabilizer, Neural network, Radial basis function, Simulink/Neural network toolbox.

1. INTRODUCTION

Modern electrical power system (EPS) is characterized by extensive interconnections and increasing dependence on control for optimum utilization of existing resources. The supply of stable, reliable and economic electric energy is a major determinant of industrial progress and consequent rise in the standard of living the world over. The need for improved power availability and power quality has been increasing over the years. Stability of power systems has been and it will continue to be the major concern in power system operations.

The high gain and fast action of excitation system produces the negative damping torque to the rotor of the synchronous generator. The controller referred as power system stabilizer (PSS) is desired to be connected with synchronous generator to compensate the negative effect of fast action and high gain of automatic voltage regulator (AVR) and other sources of negative damping [1,2].

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 [1-8]. 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 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 [1, 6], consists of three stages namely a phase compensation stage, a signal 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, 9-11]. 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 [1, 2, 10-11].

The PSSs mostly discussed/proposed in literature are useful for fixed working conditions. The gain settings of these PSSs are obtained at specified operating conditions which are a challenge for varying loading conditions. The problem of instability may be created if these loading conditions change from one value to another.

1.1. Literature Review (Power System Stabilizer)

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

1.1.1. Conventional PSS: Heffron and Phillips [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* [2] in this respect 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.

Chan and Hsu [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* [10] proposed a criterion for designing a PSS, to cancel the negative damping torque produced in a synchronous machine and AVR.

Yuan and Chang [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 [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 [15] proposed a self-tuning PID-PSS for multi-machine system.

P. Kundur [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.

1.1.2 Classification based on artificial intelligent (AI) techniques: 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 discussed by Lokman [16].

1.1.2.1. *Artificial neural network and fuzzy logic based PSS:* Wu and Hsu [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* [18] suggested adaptive ANN PSS and Liu *et al* [19] designed an indirect adaptive neural network based PSS (INDC) consisting of a neuro-identifier and a neuro-controller.

Majid *et al* [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 [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 [22] proposed fuzzy logic based PSS for increasing stability of two area four machine system.

1.1.2.2 *Optimization based intelligent techniques:* These techniques include genetic algorithm (GA), particle swarm optimization (PSO), Tabu search (TS) etc. Abido *et al* [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 [24] proposed the particle swarm optimization based PSS for self-tuning of parameters of PSS. Haddin *et al* [25] proposed PSO based coordination of AVR-PSS and AGC for improving the dynamic stability of the generator and in addition, Hemmati *et al* [26] proposed PID-PSS based hybrid genetic algorithm for SMIB.

1.2.2.3 *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 [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 [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 *et al* [29] proposed the tuning optimal parameter of neuro-fuzzy PSS technique with genetic algorithm on SMIB.

2. PROBLEM STATEMENT AND SUGGESTED SOLUTIONS

The power system stabilizers mostly discussed in literature are useful for fixed working conditions [30-32]. 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 value.

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 [31-32].

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 [33]. 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 [34-36]. 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 [31-36].

Feedforward neural network based PSS is proposed in this research work. Popular type of FFNN known as “radial basis function” (RBF) network with orthogonal least square (OLS) learning algorithm is proposed. The simulations results using Matlab/Simulink and neural network toolbox are compared and discussed in detail with conventional, PID and proposed RBFNN power system stabilizer.

3. MODEL OF POWER SYSTEM FOR PROPOSED METHODOLOGY

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, 31-32] popularly known as single synchronous machine (generator) connected to an infinite bus (SMIB) system. Figure 1 shows the equivalent circuit of SMIB.

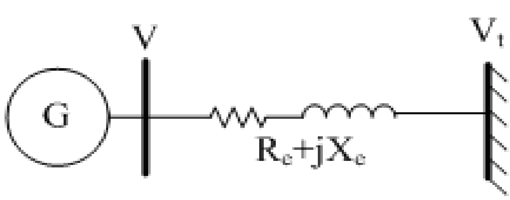

Fig. 1: A single synchronous machine connected to an infinite bus (SMIB)

The linearized model of synchronous generator and excitation system developed based on the linear model and he linearized equations for the synchronous machine are given by (the Δ subscripts are dropped for convenience) and briefly explained in [1-8, 31-32].

The complete state-space model of the synchronous generator with excitation system with state variables and V_{REF} and T_m are the driving functions by assuming that V_S is zero. For all operating conditions, the power system dynamics and PSS can be modeled by a set of nonlinear differential equation as [1-8, 31-32]:

$$\dot{X} = f(X,U)$$

By linearizing, the small signal analysis can be achieved:

$$\dot{X} = AX + BU$$

The voltage regulator is often assumed to introduce negative damping and 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 (power system stabilizers) network” [1, 31-32]. To obtain the error fed to the AVR controller, stabilizing signals of PSSs are injected in excitation systems at the summing point where terminal voltage and reference voltage are added. Such PSS signal V_s generally obtained from speed/frequency deviation and is processed through a suitable network to obtain the desired phase relationship. Figure 2, shows this schematic arrangement.

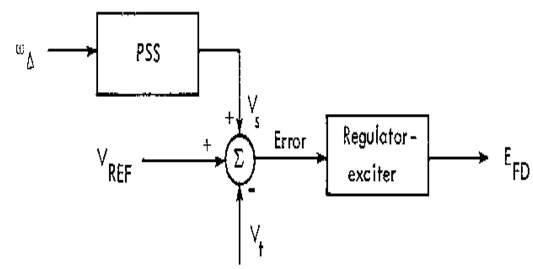

Fig. 2: Schematic arrangement of PSS

The PSS is a feedback element from the shaft speed and mathematically is represented as:

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

The washout compensation effect after a time lag τ_0, with typical values of 4sec to 20-30 sec is considered [1, 31-32]. This is reset control which assures no permanent deviation in

$$A = \begin{bmatrix} -\frac{D}{2H} & -\frac{K_1}{2H} & -\frac{K_2}{2H} & 0 & 0 & 0 \\ \omega & 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{K_4}{T'_{do}} & -\frac{1}{T'_{do}K_3} & -\frac{1}{T_E} & 0 & 0 \\ 0 & -\frac{K_E K_5}{T_E} & -\frac{K_E K_6}{T_E} & -\frac{1}{T_E} & 0 & -\frac{K_E}{T_E} \\ 0 & -\frac{K_{STAB}K_1}{2H} & -\frac{K_{STAB}}{2H} & 0 & -\frac{1}{T_w} & 0 \\ 0 & -\frac{K_{STAB}K_1}{2HT_1} & -\frac{K_{STAB}K_2}{2HT_2} & 0 & -\frac{T_w - T_1}{T_w T_2} & -\frac{1}{T_2} \end{bmatrix}$$

the terminal voltage for a prolonged error in a frequency, such as might be in an overload condition. The second component shown in equation (7) represents 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 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. The PSS produces positive component of damping torque that is in phase with the frequency deviation and used to compensate negative damping in rotor which requires a phase-lead circuit for compensating the phase-lag between exciter input and the resulting electrical torque. For this purpose a high-pass filter (HPF) is used in the signal washout component. It blocks steady state variations in the angular frequency from varying the field exciter voltage [1, 31, 32].

The complete linearized block model of synchronous generator including automatic voltage regulator and PSS is shown in Figure 3 and 4 (two prevalent perspectives) with the parameters and numerical values mentioned in [1, 31, 32]. The input to the proposed power system stabilizer is speed/frequency and output is applied at the summing junction of the reference voltage.

4. DESIGNING METHODOLOGY OF RBF NEURAL NETWORK

4.1 DESIGN:

In this methodology, an orthogonal least squares (OLS) algorithm of RBF automatically chooses a suitable number of neurons in the hidden layer of a RBF network from a set of input data.

The 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 other types of feedforward neural networks.

A radial basis function network can be utilized to approximate a function. The neurons are attached to the hidden layer until it meets the precise mean square error goal. In case of training of RBF network, the below steps in MATLAB software are repeated until the network's mean square error falls below the goal [32].

- To find the input vector with the greatest error.
- A radial basis (radbas) transfer function neuron is added with weights equal to the vector of step 2.
- The linear (pureline) transfer function layer weights are redesigned to minimize error.
- It is found that Nineteen (19) neurons are created in the hidden layer.
- One (01) neuron or node with linear transfer function is used in the output layer.
- Error goal is 0.00001
- Spread constant is 1.4

4.2 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 Figures 6-9.

4.2.1 At normal loading conditions

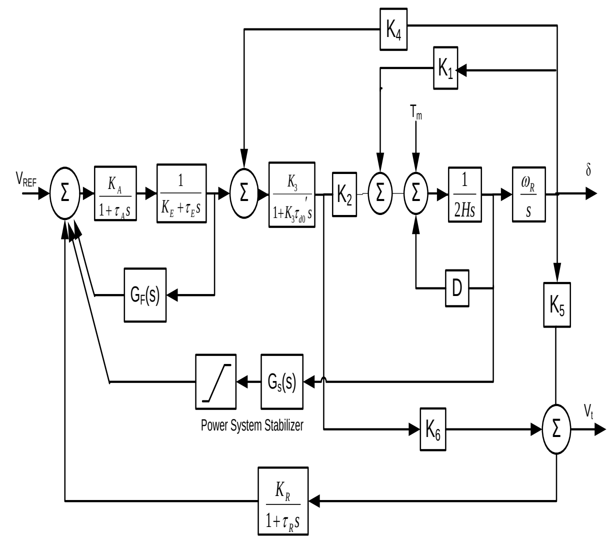

Fig. 3: Overall block diagram of SMIB with PSS

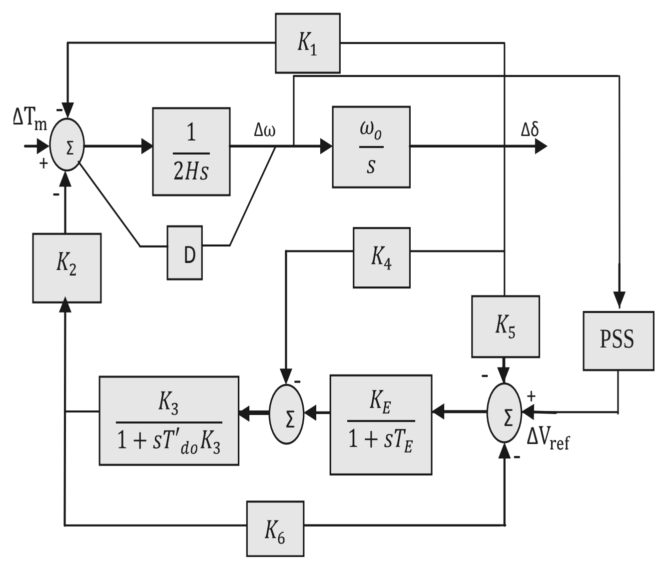

Fig. 4: Overall block diagram of SMIB with PSS

Figure 5 shows the RBF architecture structure after training and achieving simulation model of RBF network.

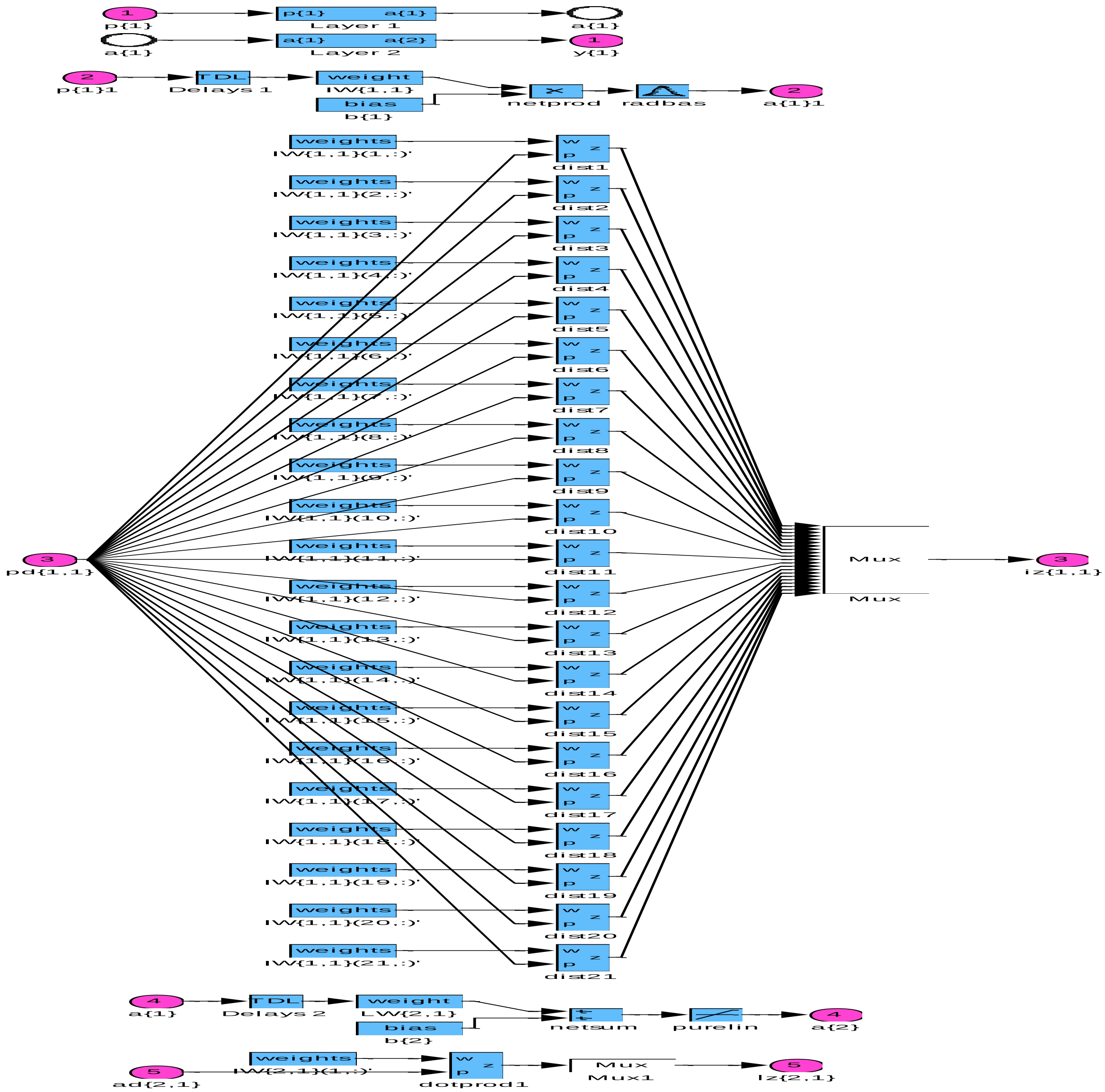

Fig. 5: RBF architecture structure after training and achieving simulation model of RBF network

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.

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).

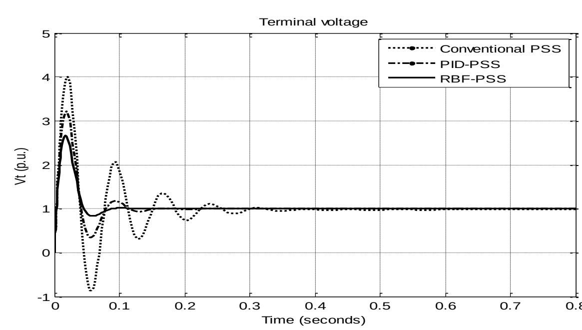

Fig. 6: Combined response of terminal voltage with CPSS, PID and RBF-PSS

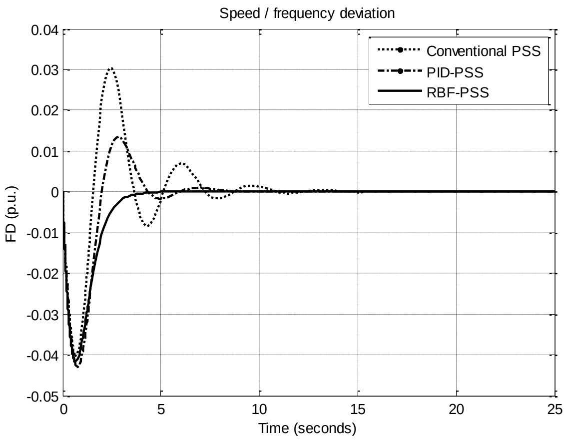

Fig. 7: Combined response of frequency deviation with Conventional, PID and RBF PSS

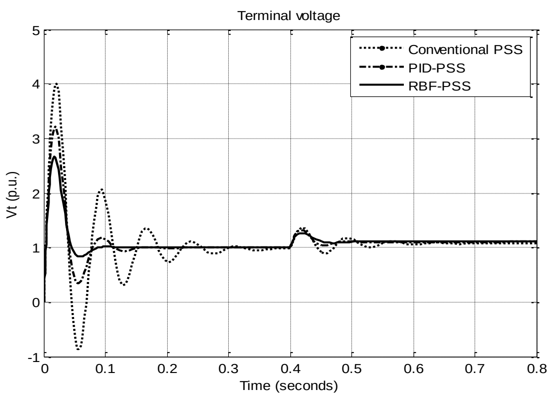

Fig. 8: Combined response of terminal voltage with CPSS, PID and RBF PSS

4.2.2 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.

Dynamic performance of frequency deviation

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

5. COMPARISON OF RESULTS

From a detailed discussion on the results obtained by applying FFNN RBF network it is clear that the performance of the RBF networks is better than the conventional type PSSs. The RBF networks have favorable characteristics of the best approximation property and a compact network structure. The RBF networks have a faster training time than MLP networks as described in [new paper of JBASR]. However, RBF networks require more hidden layer neurons than MLP networks [32]. The architectures of RBF networks are shown in below Table 1.

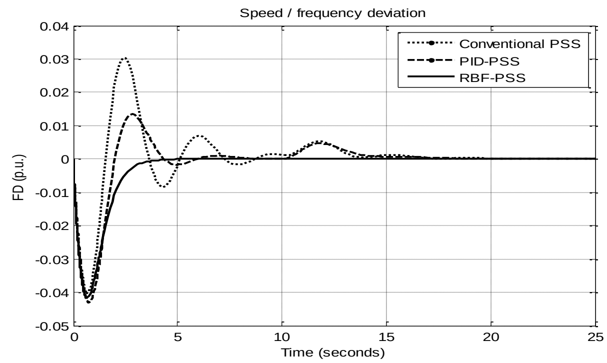

Fig. 9: Combined response of frequency deviation with Conventional, PID and proposed RBF-PSS after 10% change in load

Table 1: The architectures of RBF networks

Type of NN	Time required for training	Number of neurons		Transfer function		SSE
		1st layer	2nd Layer	1st Layer	2nd Layer	
RBF	6 sec	19	01	radbas	purelin e	1e-6

Table 2: The rise time, settling time and p. u overshoot comparisons of PSSs in case of frequency deviation responses

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
RBFPSS	2.6	3.5	0.0

Tables 2 and 3 describe the comparisons of terminal voltage and frequency deviation in case of proposed types RBF network in terms of the rise, settling times and per unit overshoot of all the types of PSSs.

CONCLUSIONS

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 RBF- PSS.

Table 3: The rise time, settling time and p. u overshoot comparisons of PSSs in case of Terminal voltage responses

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
RBFPSS	0.001	0.08	2.75

Hence a PID-PSS system is developed then trained in parallel with RBF and compared the responses at trained data at operating conditions described in detail [1, 31-32]. It is desired 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.

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. Popular type of feedforward neural networks, namely radial basis function (RBF) networks has been proposed.

The simulation result indicates that the RBF-PSS control system ensures superior responses at normal as well as changing operating conditions. Comparisons of rise time, settling time and p.u overshoot shown in Tables 2 and 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.

As RBF NN yields dynamic presentation with the normal loading conditions at which they are trained and for other varying load conditions.

The particular conclusion concerned with the above architectures are outlined below

A considerable shortcoming of MLP networks [JBASR plus other my paper references] are overcome with the application of proposed RBF-PSS. Due to its distinguishing properties, simple network configuration, proficient learning process and finest estimations which 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 all the types of PSSs. 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 work has broadened our scale towards electrical power system control.

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