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Comparative Analysis of Power System Stabilizer using Artificial Intelligence Techniques

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Abstract— Power system stabilizers (PSSs) are used to enhance the damping during low frequency oscillations. The paper presents study of power system stabilizer using fuzzy logic and neural network to enhance stability of single machine infinite bus system. In this paper basic problem of conventional power system stabilizer for stability enhancement is defined which is traditionally used. Artificial intelligence techniques provide one alternative for stability enhancement and speed deviation (Δw). The proposed method using Artificial intelligence techniques achieves better improvement than conventional power system stabilizer. Fuzzy logic rules were developed for triangular membership function of input and output variables. Neuro controller is implemented and it is compared with reference model. The system is simulated in SIMULINK environment and the performances of conventional, Fuzzy based and Neural network based power system stabilizers are compared.

Keywords: Power system stabilizer; Stability; Single machine system; Fuzzy logic; Neural Network; SIMULINK.

I. INTRODUCTION

Power system stability is a property of a power system that enables it to remain in in a state of operating equilibrium under normal operating conditions. Small signal and transient are two categories of stability. Small signal stability is the ability of the system to return to a normal operating state following a small disturbance. Transient stability is the ability of the system to return a normal operating state following a severe disturbance, such as a single or multi-phase short-circuit or a generator loss.

Low frequency oscillations are a major problem in large power system. A power system stabilizer provides supplementary control signal to the excitation system of electric generating unit for damping these low frequency oscillation. Power system stabilizers are successfully used in power systems for few years because of their flexibility low cost and easy implementation.

The power system stabilizer is used to generate supplementary control signal in order to dampen the low frequency oscillation. The conventional power system stabilizer is widely used in existing power system and has contributed to the enhancement of the dynamic stability of power systems [3].

The parameters of conventional power system stabilizer are based on linearized model of power system around of nominal operating point. Power systems are highly nonlinear systems so the design of conventional power system stabilizer based on linearized model of the power systems cannot guarantee its performance in practical operating environment [4].

To improve the performance of conventional power system stabilizer many techniques have been proposed for the design for example genetic algorithm, neural network, simulated annealing fuzzy logic and many other intelligent optimization techniques. From last few years fuzzy logic controller is used in power system applications as a powerful tool.

The paper presents the performance of single machine infinite bus system with fuzzy power system stabilizer of triangular membership function. Here we have taken speed deviation (Δw) and acceleration as input variables then performance of fuzzy based power system stabilizer with triangular membership function and neural network based power system stabilizer are studied and compared with conventional lead-lag compensator. The simulations are implemented in SIMULINK environment.

II. SYSTEM DESIGN

The system consists of synchronous machine, excitation system and power system stabilizer.

1) *Synchronous Machine Model:*

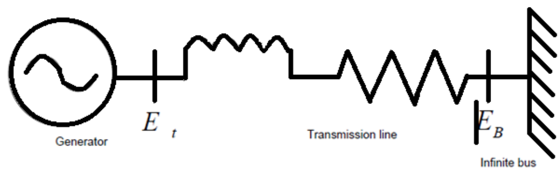

Fig.1: Synchronous Machine Connected To Infinite Bus

Fig.1 shows the synchronous machine connected to infinite bus through transmission line.

2) *Excitation System:*

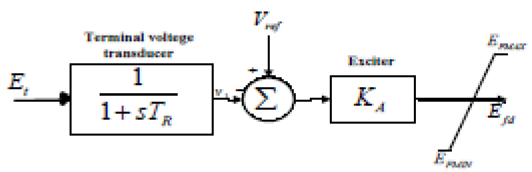

Fig. 2: Block diagram of excitation system

Excitation system is capable of responding rapidly to a disturbance so as to enhance transient stability and of modulating the generator field so as to enhance small scale stability. The duty of an exciter is to provide necessary field current in rotor winding of an alternator. Terminal voltage transducer senses generator terminal voltage rectifies and filters it to dc quantity. Exciter provides dc power to synchronous machine field winding, constituting the power angle of excitation system.

3) Power System Stabilizer (PSS):

Power system stabilizers (PSS) were developed to aid in damping these oscillations via modulations of excitation system of generator s. The action of a PSS is to extend the angular stability limits of a power system by providing supplemental damping to the oscillation of synchronous machine rotors through the generator excitations.

III. CONVENTIONAL POWER SYSTEM STABILIZER

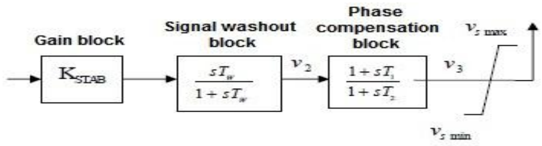

Fig. 3: Block Diagram of Conventional PSS

The basic structure of conventional PSS is shown in figure (3). It contains three components: phase compensation block, signal washout block and gain block. The phase lag between exciter input and generator electrical output provides by phase compensation block with appropriate phase lead characteristic. The signal washout block serves as high pass filter. The stabilizer gain K_{st} determines the amount of damping.

IV. FUZZY LOGIC BASED PSS

The variables chosen for this controller are speed deviation, acceleration and voltage. In this, the speed deviation and acceleration are the input variables and voltage is the output variable. The number of linguistic variables describing the fuzzy subsets of a variable varies according to the application. Usually an odd number is used. A reasonable number is seven. However, increasing the number of fuzzy subsets results in a corresponding increase in the number of rules. Each linguistic variable has its fuzzy membership function. The membership function maps the crisp values into fuzzy variables. The triangular membership functions are used to define the degree of membership. It is important to note that the degree of membership plays an important role in designing a fuzzy controller.

Each of the input and output fuzzy variables are assigned seven linguistic fuzzy subsets varying from negative big (NB) to positive big (PB). Each subset is associated with a triangular membership function to form a set of seven membership functions for each fuzzy variable.

Nb	Negative big
Nm	Negative medium
Ns	Negative small
Ze	Zero
Ps	Positive small
Pm	Positive medium
Pb	Positive big

Table. 1: Membership functions for fuzzy variables

A. Fuzzy Rule Base:

A set of rules which define the relation between the input and output of fuzzy controller can be found using the available knowledge in the area of designing PSS. These rules are defined using the linguistic variables. The two inputs, speed and acceleration, result in 49 rules for each machine. The typical rules are having the following structure:

1) Rule 1: If speed deviation is NM (negative medium) AND acceleration is PS (positive small) then voltage (output of fuzzy PSS) is NS (negative small).

2) *Rule 2:* If speed deviation is NB (negative big) AND acceleration is NB (negative big) then voltage (output of fuzzy PSS) is NB (negative big).

3) Rule 3: If speed deviation is PS (positive small) AND acceleration is PS (positive small) then voltage (output of fuzzy PSS) is PS (positive small). And so on.

All the 49 rules governing the mechanism are explained in table 2 where all the symbols are defined in the basic fuzzy logic terminology.

Speed Deviation	Acceleration						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NM	NS
NM	NB	NM	NM	NM	NS	NS	ZE
NS	NM	NM	NS	NS	ZE	ZE	PS
ZE	NM	NS	NS	ZE	PS	PS	PM
PS	NS	ZE	ZE	PS	PS	PM	PM
PM	ZE	PS	PS	PM	PM	PM	PB
PB	PS	PM	PM	PB	PB	PB	PB

Table 2: Fuzzy rules

The stabilizer output is obtained by applying a particular rule expressed in the form of membership functions. Finally the output membership function of the rule is calculated. This procedure is carried out for all of the rules and with every rule an output is obtained. Using min-max inference, the activation of the i^{th} rule consequent is a scalar value (Vs) which equals the minimum of the two antecedent conjuncts' values. For example if speed deviation belongs to NB with a membership of 0.3 and acceleration belongs to NM with a membership of 0.7 then the rule consequence i.e. Voltage signal (Vs) will be 0.3.

Using fuzzy rules shown in table 2, Conventional PSS is replaced in Fuzzy controller block.

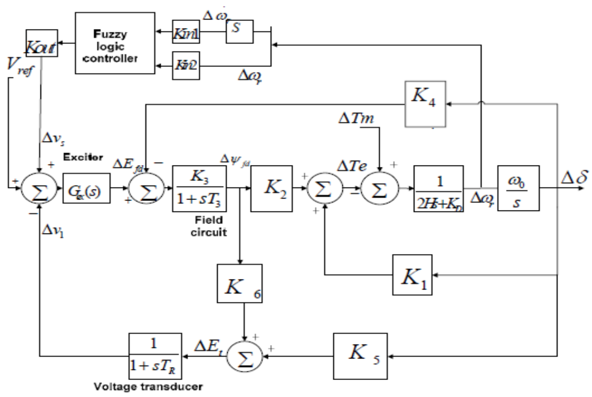

Fig. 4: Block diagram of fuzzy logic controller implemented on single machine infinite bus system

The figure 4 shows the diagram of the representation of fuzzy based controller for single machine infinite bus system. Here the angular velocity and its derivative are inputs and voltage is output. K_{in1}, K_{in2} and K_{out} are gains which normalize inputs and output according to the range in which the membership functions are defined. The gain parameters are tuned to give the desired response.

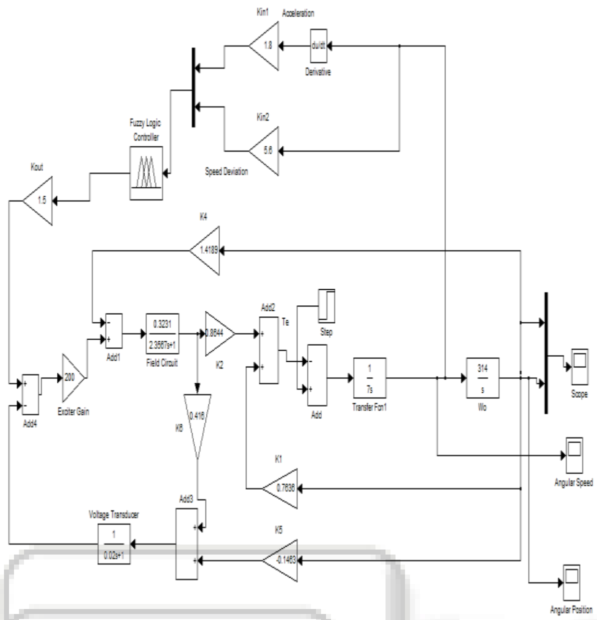

Fig. 5: Simulink model with Fuzzy Logic Based PSS

V. NEURAL NETWORK BASED PSS

The basic objective of a controller is to provide the desired output for any system Since neural networks have learning and self-organizing abilities allowing them to adapt changes in data, the input-output data necessary for the off- line training of the neural network have been obtained in the present work using reference and plant models. Trials have been carried to obtain maximum accuracy with minimum number of neurons per layer. The feed forward neural network controller developed consists of three layers, with one neuron in the input layer, 20 neurons in the hidden layer and one neuron in the output layer. The activation function used for the hidden layer is bipolar sigmoid while the activation function of the output layer is linear Back propagation algorithm is used for training of the created network. This algorithm is the most popular supervised learning rule for multi- layer feed forward networks. Quasi-Newton method applied for updating weights is a one-dimensional minimization related numerical interpolation method which has a fast convergence property known as quadratic convergence and hence it exhibits super linear convergence near target. With back propagation algorithm, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training". [11, 12]

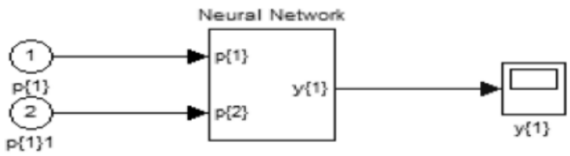

Fig. 6: Simulink block of Neuro -controller

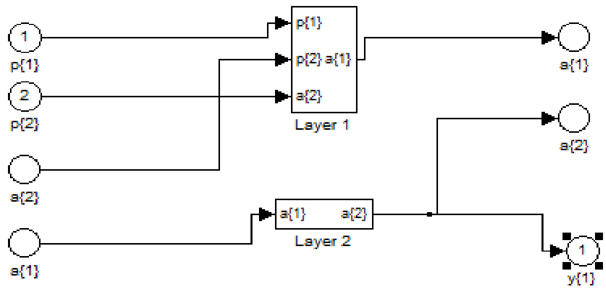

Fig. 7: Simulink block of neural network used as a Neuro-controller

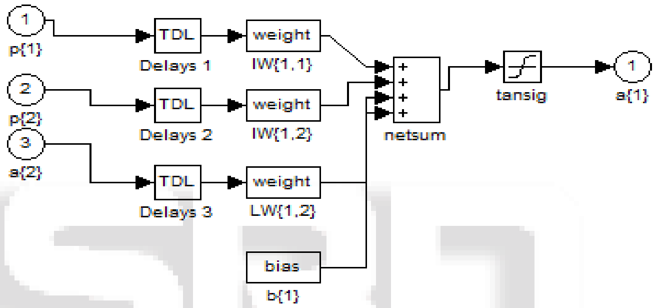

Fig. 8: Simulink block of input and hidden layer of Neuro -controller

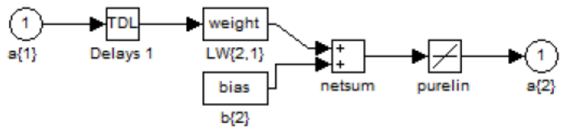

Fig. 9: Simulink block of output layer of Neuro- controller

VI. RESULT ANALYSIS

Figure 10, 11 and 12 shows Speed deviation versus time when K_D=0. when the system get disturbaces, it become stable after some oscillation. As figure 11 shows in fuzzy based PSS, the damping of oscillation is better compared to CPSS. In Neural based PSS, the damping of oscillation is better compared to CPSS & FPSS as shown in figure 12.

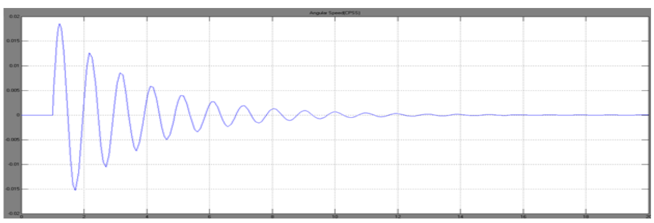

Fig. 10: Speed Deviation versus time (CPSS)

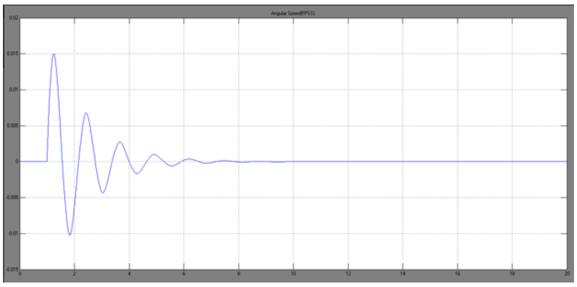
Fig. 11: Speed deviation versus time (FPSS)

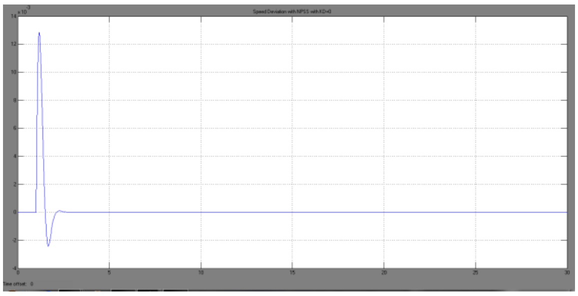
Fig. 12: Speed deviation versus time (NPSS)

VII. CONCLUSION

The Matlab/Simulink simulation shows that the neural controller has an excellent response with very small oscillation than fuzzy based PSS and conventional PSS. Conventional power system stabilizer (CPSS) response shows a ripple and reaching steady state operating point after some oscillations. From the results in figure 10, 11 and 12 following observations are made:

Controller used	Peak time	Settling time (sec)
CPSS	0.0175	11
FPSS	0.014	6.2
NPSS	0.0125	2.48

Table. 3: Comparison of CPSS, FPSS and NPSS

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