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Genetic Algorithm Based Design of Fuzzy Logic Power System Stabilizers in Multimachine Power System

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***Abstract*—**This paper presents an approach for the design of fuzzy logic power system stabilizers using genetic algorithms. In the proposed fuzzy expert system, speed deviation and its derivative have been selected as fuzzy inputs. In this approach the parameters of the fuzzy logic controllers have been tuned using genetic algorithm. Incorporation of GA in the design of fuzzy logic power system stabilizer will add an intelligent dimension to the stabilizer and significantly reduces computational time in the design process. It is shown in this paper that the system dynamic performance can be improved significantly by incorporating a genetic-based searching mechanism. To demonstrate the robustness of the genetic based fuzzy logic power system stabilizer (GFLPSS), simulation studies on multimachine system subjected to small perturbation and three-phase fault have been carried out. Simulation results show the superiority and robustness of GA based power system stabilizer as compare to conventionally tuned controller to enhance system dynamic performance over a wide range of operating conditions.

***Keywords*—**Dynamic stability, Fuzzy logic power system stabilizer, Genetic Algorithms, Genetic based power system stabilizer.

I. Introduction

THE application of power system stabilizers for improving dynamic stability of power systems and damping out the low frequency oscillations due to disturbances has received much attention [1-3]. The conventional PSS comprising a cascade connected lead-lag network with rotor speed deviation as input has made great contribution in enhancing system stability [4]. However, the performance of the CPSS becomes sub-optimal following variations in system parameters and loading conditions [2]. Power system is a highly nonlinear system and it is difficult to obtain exact mathematical model of the system. In recent years, adaptive self tuning, variable structure, artificial neural network based PSS, fuzzy logic based PSS have been proposed to provide optimum damping to the system oscillations under wide variations in operating conditions and system parameters [6-8].

Recently, Fuzzy logic power system stabilizers (FLPSS) have been proposed to overcome this problem [8,9,10]. Fuzzy logic makes complex and non-linear problems much easier to solve by allowing a more natural representation of the situations being dealt with. Fuzzy Logic control appears to possess many advantages like lesser computational time and robustness. It has been shown that fuzzy logic is one of the best approaches for non-linear, time varying and ill-defined systems. Fuzzy logic based power system stabilizer has been applied successfully for the enhancement of dynamic stability of power system [9-10]. The application of fuzzy logic power system stabilizer improves the damping of the system oscillations. However, optimum tuning of the parameters of FLPSS further required for better performance under wide variation of system operating conditions. Although, fuzzy logic controllers showed promising results, they are subjective and heuristic. There is no systematic design procedure for the tuning of the parameters of fuzzy logic power system stabilizer. The generation of membership functions and the selection of scaling factors have been done either, by trial-and-error, iteratively, or by human experts. Therefore, the design of fuzzy logic power system stabilizer (FLPSS) becomes a time consuming and laborious task.

Genetic algorithms (GA) are search algorithms based on the mechanics of natural selection and survival-of-the-fittest [5]. GAs is optimization procedures that were devised on population genetics. The recent approach is to integrate the use of GA and fuzzy logic systems in order to design power system stabilizer [11,-13]. GA has been applied successfully in the design of power system stabilizers [14,15,16]. The performance of FLPSS can be significantly enhanced by incorporating genetic-based learning mechanism. The advantage of the GA technique is that it is independent of the complexity of the performance index [17-19].

This paper deals with the design method for the stability enhancement of a multimachine power system using FLPSSs whose parameters are tuned using genetic algorithm. The proposed tuning scheme uses a GA based search that integrates a classical parameter optimization criterion based on Integral of Squared Time Squared Error (ISTSE).

All parameters including Fuzzy logic gains centers of membership functions and variance of Gaussian membership functions.

II. System Model

In this study a two area, 11-bus, 4-machine system is considered. Each synchronous machine is represented by non-linear sixth-order model as in the [3]. It is assumed that all the 4 generators are equipped with static excitation systems.

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All the four generators are provided with IEEE Type ST1A model of excitation system and turbine governors. The nominal system parameters and data are given in Appendix. The system used in the analysis is a two area system .The generators 1 and 2 are considered to form one area and generators 3 and 4 are considered to form second area.

III. Design Algorithm

A. Selection of Input Signals

The first step in designing a fuzzy logic power system stabilizer (FLPSS) is to decide which state variables representing system dynamic performance must be taken as the input signal to FLPSS. However, selection of proper linguistic variables formulating the fuzzy control rules is very important factor in the performance of fuzzy controllers. For the present investigations generator speed deviation $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ are chosen as input signals to FLPSS. In practice, only shaft speed deviation $\Delta\omega$ is readily available. The acceleration signal can be derived from speed signals measured at two sampling instant by the following expression:

$$\Delta\dot{\omega}(kT) = \frac{[\Delta\omega(kT) - \Delta\omega(k-1)T]}{T} \quad (1)$$

B. Membership Functions

After choosing proper variables for input and output of fuzzy controllers, it is important to decide on the linguistic variables. The linguistic variables transform the numerical values of the input of the fuzzy controllers to fuzzy values. The number of these linguistic variables specifies the quality of control, which can be achieved using fuzzy controller. As the number of linguistic variables increases, the quality of control increases at the cost of increased computer memory and computational time. Therefore, a compromise between the quality of control and computational time is needed to choose the number of variables.

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For the power system under study, five linguistic variables for each of the input and output variables are used. The linguistic variables are labeled as shown in Table I.

All the investigations are carried out considering Gaussian membership functions.

A Gaussian membership is defined as:

$$f(x, \sigma_i, c_i) = \frac{e^{-(x-c_i)^2}}{2\sigma_i^2} \quad (2)$$

where, c_i is the center of the Gaussian membership function and σ_i^2 is the variance. where i = 1,2…n and n is the number of membership function. In the present investigations, the optimum value of σ and c are determined using GA.

The structure of all four FLPSS installed on each of the machine is same.

C. Rule Base

The fuzzy rules play a major role in the design of FLPSS. The rules can be generated using knowledge and operating experience with the system or understanding of the system dynamics. The two inputs, speed deviation and acceleration, generate 25 rules for each of the machine. The rules are applied to generate FLPSS output.

Table II shows the results of 25 rules, where a positive control signal is for the deceleration control and a negative signal is for the acceleration control.

TABLE I
Membership Functions

Symbol	Membership Functions
NB	negative big
NS	negative small
ZO	zero
PS	positive small
PB	positive big

The stabilizer output is determined by applying a particular rule expressed in the form of membership function. Different methods have been used for finding the output in which Minimum-Maximum and Maximum Product Methods are generally used. For present study, Min- Max method is used. Finally, the output membership function of the rule has been calculated. This is carried out for all the rules and for every rule an output membership function is obtained. In this study, Mamdani Inference engine is used.

D. Defuzzification

To obtain a deterministic control action, a defuzzification strategy is required. Defuzzification is a mapping from a space

TABLE II
Rule Base With Five Membership Functions

$\Delta\dot{\omega}$ \ $\Delta\omega$	NB	NS	ZO	PS	PB
NB	NB	NB	NB	NS	ZO
NS	NB	NS	NS	ZO	NS
ZO	NB	NS	ZO	PS	PB
PS	NS	ZO	PS	PS	PB
PB	ZO	PS	PB	PB	PB

of fuzzy control actions defined over an output universe of discourse into a space of non-fuzzy (crisp) control actions. There are different techniques for defuzzification of fuzzy quantities such as Maximum Method, Height Method, and Centroid Method. Here, COA Method has been used for defuzzification.

E. Selection of Fuzzy Variables for Optimization

The input signals are normalized using normalization factors to obtain a wide range to cover the complete universe of discourse. Similarly, a de-normalization factor is used to provide an adequate stabilizing signal. In the proposed design algorithm for FLPSS, the inner parameters of the fuzzy structure i.e., centers of membership functions and variance of the membership function are also optimized using genetic algorithm in addition to normalization and de-normalization factors for input and output signals.

IV. Optimization Technique

In this design, a genetic algorithm (GA) based search is used for the optimization of parameters of FLPSS [20]. The GA based design integrates the parameter optimization criterion based on Integral of Squared Time Squared Error (ISTSE).

An objective function that reflects small steady state error, small overshoots and oscillations has been selected for the optimization. The performance index J is defined as:

$$J_{ISTSE} = \int_0^{t_s} (\Delta\omega)^2 t^2 dt \tag{3}$$

where $\Delta\omega(t)$ is speed deviation of the generator following 5% step increase in mechanical input torque i.e., $\Delta Tm = 0.05$ p.u.

V. Design Algorithm

The sequential steps of the proposed design algorithm are presented by considering Gaussian membership functions for input and output variables. A universe of discourse, -1 to 1 is chosen and center of gravity (COG) defuzzification technique is used. The design algorithm consists of the following steps:

1) Population representation and Initialization

Genetic algorithm operates on a number of potential solutions, called a population, consisting of some encoding of the parameters set simultaneously. The chromosomes are represented in single-level binary string. In this algorithm a set of 100 individuals is generated randomly. The sizes of the individuals are dynamically reduced to the 30 individuals in the later stage of generation. This increases the convergence rate. Also, the computational time reduces since, the probability of the occurrence of good individuals increases in the first generation.

2) Objective function evaluation

The parameters of the FLPSS are tuned such that the system damping is enhanced. An ISTSE technique is used be minimize an objective function having the constraints on the parameter of the FLPSS. The objective function is defined as in equation (3).

3) Fitness functions assignment

The fitness function is used to transform the objective function value into a measure of relative fitness. The fitness function transforms the value of objective function to a non-negative. The mapping is required whenever the objective function is to be minimized as the lower objective function values correspond to fitter individuals. In this study, fitness function transformation is linear. The transformation offsets the objective function, which is susceptible to rapid convergence.

4) Selection

Selection is the process of determining the number of trials for a particular individual for reproduction and, thus, the number of offspring that an individual will produce. The roulette wheel selection method is used in this study.

5) Recombination

This is a basic operator for producing new chromosomes in the genetic programming. Crossover, produces new individuals that have some parts of both parent's genetic properties. The uniform single-point crossover is used in this study.

6) Mutation

In natural evolution, mutation is a process where one allele of a gene is replaced by another to produce a new genetic structure. A mutation probability of 0.001 is considered.

7) Reinsertion

After the operation of selection and recombination of individuals from the old population, the fitness of the individuals in the new population may be determined. The new individuals are inserted to maintain the size of the original population.

8) Termination of GA

The GA is a stochastic search method; it is difficult to specify the convergence criteria. As the fitness of a population may remain static for a number of generations before a superior individual is found, the application of termination criteria becomes problematic. The termination of the GA has been done after prespecified number of generation is reached. The process iterates till the termination criteria has not met.

The performance index J of the GA based ISTSE optimization method in different stages of the genetic search process is shown in Fig.1.

VI. Performance Analysis

The dynamic performance of four -machine system has been analyzed with the proposed GA based fuzzy logic power system stabilizer (GFLPSS), conventional PSS (CPSS) and without PSS under various disturbances. The performance of the proposed GA based fuzzy logic power system stabilizers (GFLPSSs) have been examined under small perturbation and three-phase fault at different system loading conditions. Power system toolbox (PST), MATLAB has been used for the analysis [21]. In order to test the robustness of GA based fuzzy logic power system stabilizer (GFLPSS) to enhance system damping over a wide range of operating conditions,

three loading conditions were considered: a light load, a nominal load, a heavy load.

A. Small perturbation Test

A 5% step decrease in V_{ref1} i.e. ΔV_{ref1} = -0.05 p.u. and 5% step increase in V_{ref3} = 0.05 p.u. was applied at different loading conditions. The dynamic responses of the GA based FLPSS (GFLPSS) are compared with the conventionally tuned CPSS and No PSS in the system. It is clear from the results that the damping to the system oscillations improves with the proposed GFLPSS as compare to CPSS and No PSS. Simulation results reveal that without any PSS in the system, the system oscillations are sustained, where as with GA based FLPSS oscillations are damped very quickly. The GFLPSS has a lower peak off-shoot and smaller oscillations. It is clearly shown in Fig. 2 & 3 that GFLPSS effectively and efficiently damp oscillations in the local as well as inter-area mode under small disturbance. The dynamic responses for $\Delta \omega_{12}$, $\Delta \omega_{34}$, $\Delta \omega_{13}$ and $\Delta \omega_1$, $\Delta \omega_2$, $\Delta \omega_3$, $\Delta \omega_4$ considering small perturbation of V_{ref1} = -0.05 p.u. and V_{ref3} = 0.05 p.u. for heavy loading conditions in Figs 4-5 respectively. The dynamic responses for $\Delta \omega_{12}$, $\Delta \omega_{34}$, $\Delta \omega_{13}$ and $\Delta \omega_1$, $\Delta \omega_2$, $\Delta \omega_3$, $\Delta \omega_4$ considering small perturbation of V_{ref1} = -0.05 p.u. and V_{ref3} = 0.05 p.u. for light loading conditions in Figs 6-7 respectively.

B. Large Disturbance Test

To investigate the effectiveness of the GPSS under more severe conditions, A 3-cycle, three phase fault was applied at bus 7 at t = 0.5 sec for nominal, light and heavy system loading conditions. The fault is cleared by tripping the faulty line. It can be clearly seen from Figs.8-12 that the proposed GFLPSS minimize the oscillations in speed deviation and improve the settling time and peak offshoot following a three-phase fault at different loadings. The GFLPSS provide superior performance as compare to conventional power system stabilizer in terms of settling time. The system oscillations are increasing in magnitude without any PSS in the system.

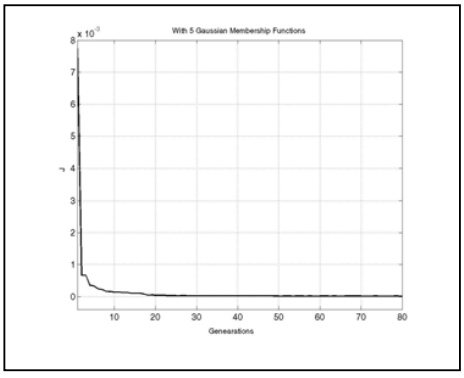

Fig. 1 Variation of performance index J of best individual

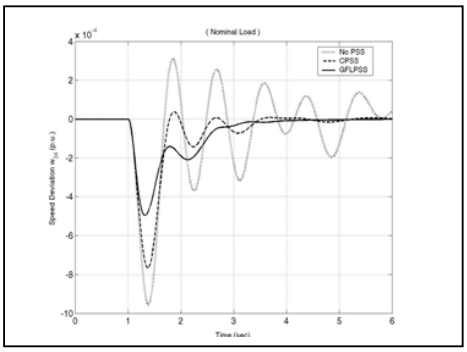

Fig. 2 Dynamic response for Δω34 considering ΔVref 1 = - 0.05 p.u.and ΔVref 3 = 0.05 p.u. for nominal load (local mode)

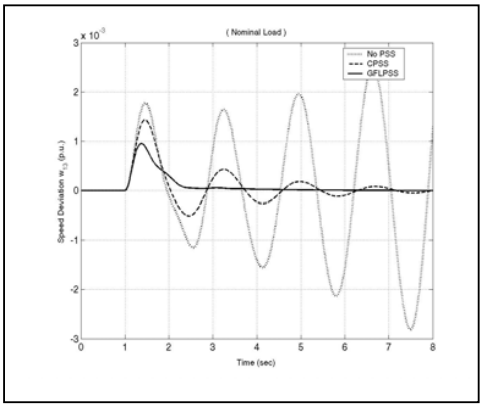

Fig. 3 Dynamic response for Δω13 considering ΔVref - 0.05 p.u.and ΔVref 3 = 0.05 p.u. for nominal load (Interarea mode)

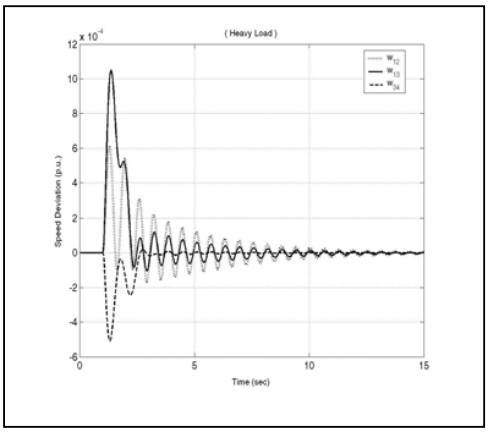

Fig. 4 Dynamic response for Δω12 , Δ ω34 , Δ ω13 considering ΔVref 1 = - 0.05 p.u.and ΔVref 3 = 0.05 p.u. for heavy load conditions with GFLPSS

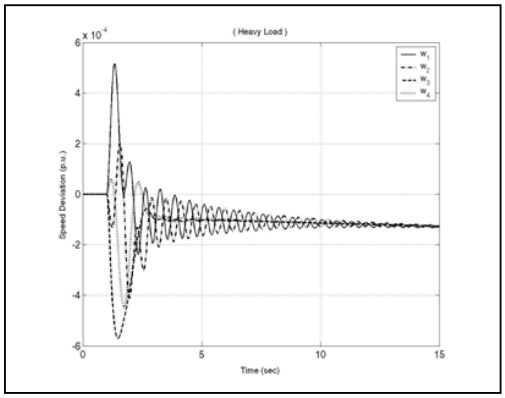

Fig. 5 Dynamic response for Δ ω1 , Δ ω2 , Δ ω3 and Δ ω4 considering Vref1 = -0.05 p.u. and Vref3 = 0.05 p.u. for heavy loading conditions

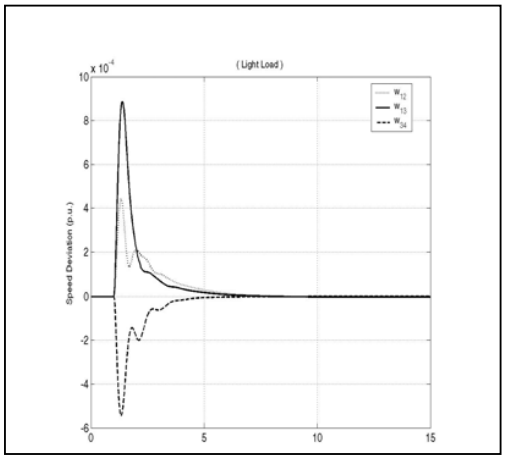

Fig. 6 Dynamic response for Δω12 , Δ ω34 , Δ ω13 considering Vref 1 = - 0.05 p.u.and Vref 3 = 0.05 p.u. for light load conditions with GFLPSS

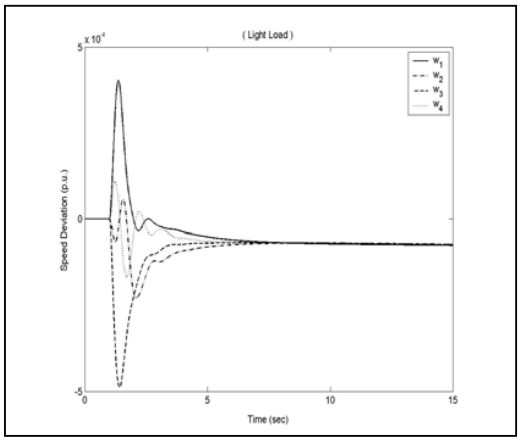

Fig. 7 Dynamic response for Δ ω1 , Δ ω2 , Δ ω3 and Δ ω4 considering Vref1 = -0.05 p.u. and Vref3 = 0.05 p.u. for light loading conditions with GFLPSS

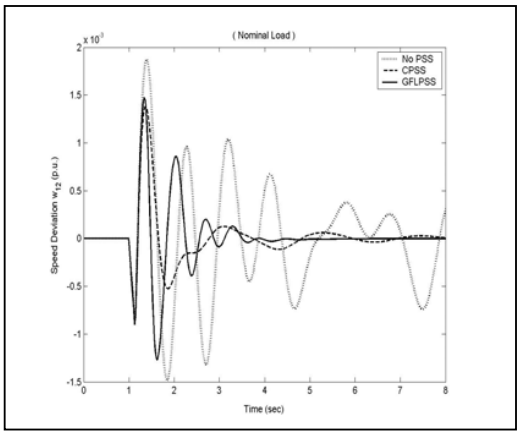

Fig. 8 Dynamic response for Δω12 following three phase, 3-cycle fault at bus-7 of for nominal loading conditions (local mode)

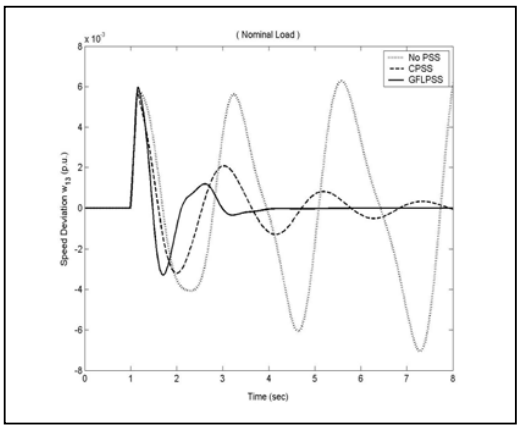

Fig. 9 Dynamic response for Δω13 following three phase, 3-cycle fault at bus-7 of for nominal loading conditions (Interarea mode)

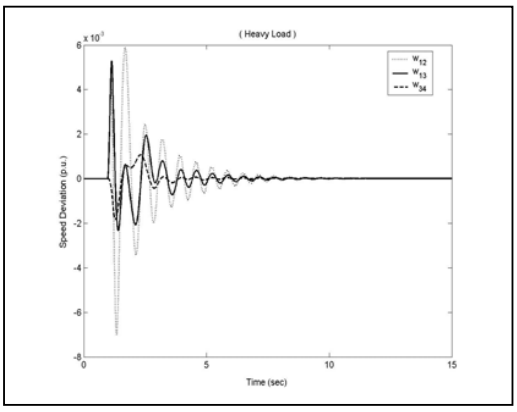

Fig. 10 Dynamic response for Δω12 , Δ ω34 , Δ ω13 considering transitory 3-phase fault at bus-7 of three cycles duration for heavy loading conditions with GFLPSS

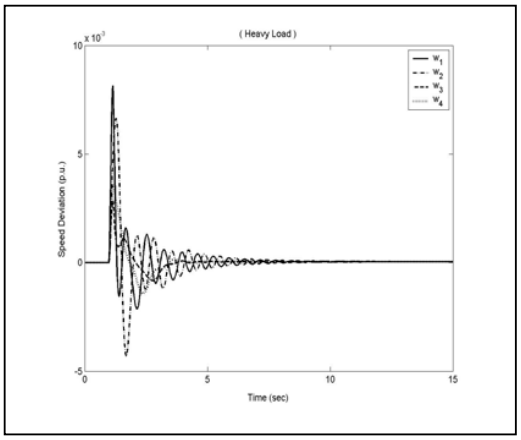

Fig. 11 Dynamic response for Δ ω1 , Δ ω2 , Δ ω3 and Δ ω4 considering transitory 3-phase fault at bus-7 of three cycles duration for heavy loading conditions with GFLPSS

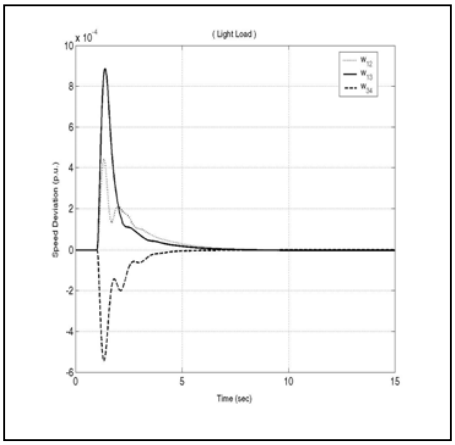

Fig. 12 Dynamic response for Δω12 , Δ ω34 , Δ ω13 considering Vref 1 = - 0.05 p.u.and Vref 3 = 0.05 p.u. for light load conditions with GFLPSS

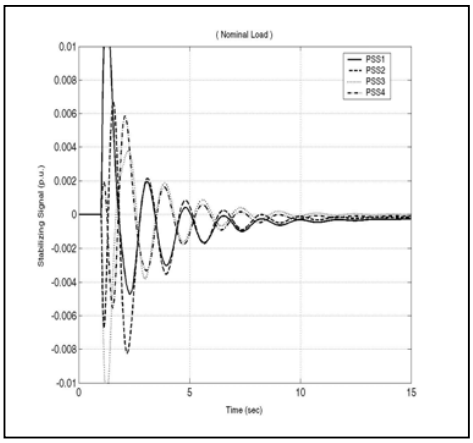

Fig. 13 Stabilizing signal under small perturbation with CPSS

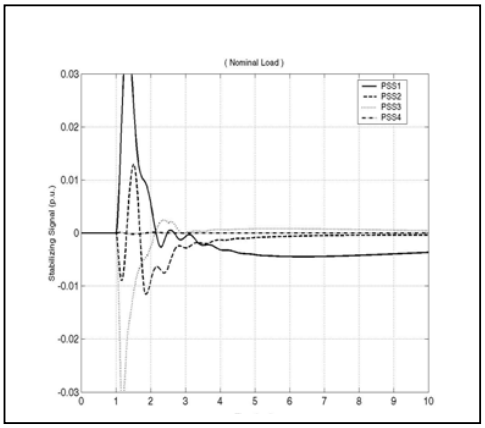

Fig. 14 Stabilizing signal under small perturbation with GFLPSS

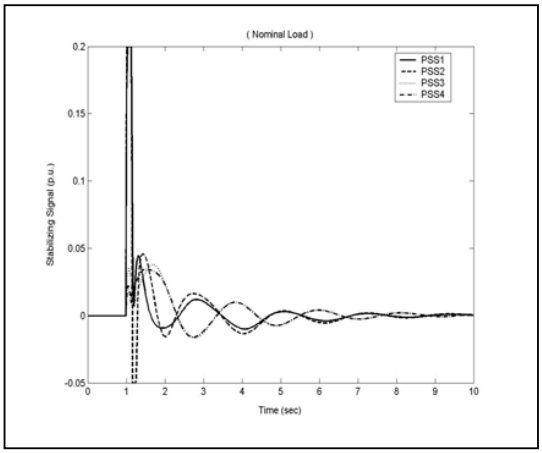

Fig. 15 Stabilizing signal under three-phase fault with CPSS

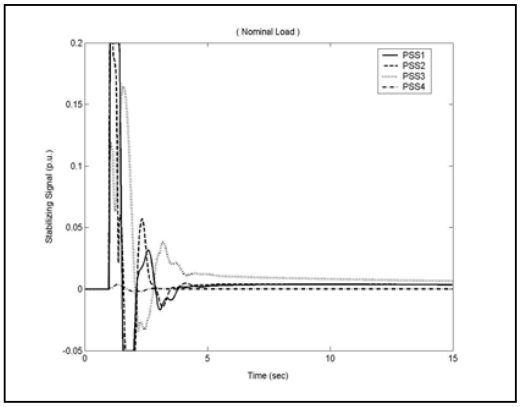

Fig. 16 Stabilizing signal under three-phase fault with GFLPSS

The stabilizing signals under small perturbation for nominal loading condition with conventional PSS and GA based FLPSS are shown in Fig.13 and Fig. 14 respectively.

The stabilizing signal considering transitory 3-phase fault at bus-7 of three cycles duration for nominal loading conditions with conventional PSS and GA based FLPSS are shown in Fig.15 and Fig. 16 respectively.

The results shown clearly indicate that GFLPSS provide effective stabilizing signal than CPSS under small disturbance.

Simulation results reveal that the performance of the fuzzy logic power system stabilizers can be significantly improved by incorporating the genetic-based learning mechanism for tuning all parameters including FLPSS gains centers of membership functions and variance of Gaussian membership functions.

VII. Conclusions

This paper presents a method for the design of fuzzy logic power system stabilizers in a multimachine power system using genetic algorithm. A systematic approach for tuning the parameters of fuzzy logic power system stabilizer using ISTSE technique has been presented. The design algorithm for simultaneous tuning of fuzzy logic power system stabilizers has been tested for multimachine model. The performance of the FLPSS can be significantly improved by incorporating the genetic-based learning mechanism for tuning of parameters of fuzzy logic power system stabilizer. Simulation results reveal that the dynamic performance of the system enhances with genetic based fuzzy logic power system stabilizer. Investigations reveal the performance of simultaneously tuned genetic algorithm based fuzzy power system stabilizers in a multi-machine system is quite robust under wide variations in loading conditions both for small and large disturbance for local as well as interarea mode.

Appendix I

Non-linear model of Multi-machine power system:

i^{th} machine model :

$$\rho\omega_i = (T_{mi} - T_{ei}) / 2H$$

$$\delta_i = \omega_o (\omega_i - 1)$$

$$\rho E'_{q\,i} = [E_{fd\,i} - (E'_{qi} + (X_{d\,i} - X'_{di}) I_{di}) / T'_{doi}$$

$$\rho E_{fd\,i} = [K_{Ai} (V_{ref\,i} - V_{t\,i}) + v_{s\,i}) - E_{fd\,i}] / T_{ai}$$

$$T_e = E'd_i I_{di} + E'q_i I_{qi} - (X'_{qi} - X'_{di}) I_{di} I_{qi}$$

$$E = E'_{qi} - (X_d - X'_d) I_{di}$$

$$\delta_{ij} = \delta_i - \delta_j$$

Appendix II

The generation and terminal voltage of generator buses are as follows:

G1: Pe=700 MW Qe=185 MVA Vt=1.03 $\angle 20.2^o$

G2: Pe=700 MW Qe=235 MVA Vt=1.01 $\angle 10.5^o$

G3: Pe=719 MW Qe=176 MVA Vt=1.03 $\angle -6.8^o$

G4: Pe=700 MW Qe=202 MVA Vt=1.03 $\angle -17.0^o$

The loads and reactive power supplied (Q_C) by the shunt capacitors at buses 7 and 9.

Bus 7: P_L=967MW Q_L=100 MVAr, Q_C =200 MVAr
Bus 9: P_L=1767 MW Q_L=100 MVAr, Q_C = 350 MVAr
Excitation system K_A=50 T_R=0.01 sec.
Turbine-governor system Kg =25 Tg=0.5

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