Trends in Life Sciences
An International Peer-reviewed Journal
www.sciencejournal.in

OPTIMAL TUNING OF MULTI-MACHINE POWER SYSTEM STABILIZER PARAMETERS USING GENETIC ALGORITHM

Homayoun Ebrahimian[1], Mohammad Yazdani[2], Hamed Musazadeh[2] and Nasser yousefi[2]
1Department of Electrical Engineering, Ardabil Branch, Islamic Azad University, Ardabil, Iran
2Young Researchers and Elite club, Ardabil Branch, Islamic Azad University, Ardabil, Iran

ABSTRACT
The problem of dynamic stability of power system has challenged power system engineering since over three decades now. In a generator, the electromechanical coupling between the rotor and the rest of the system causes it to behave in a manner similar to a spring mass damper system, which exhibits an oscillatory behavior around the equilibrium state, following any disturbance, such as change in loads, change in transmission line parameters, fluctuations in the output of turbine and fault etc. Optimal tuning of multi machine Power System Stabilizers (PSSs) using genetic algorithm is presented in this paper. Selecting the parameters of power system stabilizers which simultaneously stabilize system oscillations is converted to a simple optimization problem that is solved by a genetic algorithm. The advantage of GA technique for tuning the PSS parameters is that it is independent of the complexity of performance index considered. The efficiency of the proposed method has been tested on two cases of multi-machine systems include 3-machine 9 buses system and 10-machine 39 buses New England system. The proposed method of tuning the PSS is an attractive alternative to conventional fixed gain stabilizer design as it retains the simplicity of the conventional PSS and at the same time guarantees a robust acceptable performance over a wide range of operating and system condition.

KEY WORDS: PSS Design, Genetic Optimization Algorithm, Multi-machine system, Power System Dynamics

INTRODUCTION

In early sixties, most of the generators were getting interconnected and the automatic voltage regulators (AVRs) were more efficient. With bulk power transfer on long and weak transmission lines and application of high gain, fast acting AVRs, small oscillations of even lower frequencies were observed. The stability of the system, in principle, can be enhanced substantially by application of some form of close-loop feedback control. Over the years a considerable amount of effort has been extended in laboratory research and on-site studies for designing such controllers. The problem, when first encountered, was solved by fitting the generators with a feedback controller which sensed the rotor slip or change in terminal power of the generator and fed it back at the AVR reference input with proper phase lead and magnitude so as to generate an additional damping torque on the rotor (Baster and Schaefer. 2008). Damping power oscillations using supplementary controls through turbine, governor loop had limited success. With the advent fast valving technique, there is some renewed interest in this type of control (Klofenstein, 1971). This device came to be known as a Power System Stabilizer (PSS). PSS is auxiliary control devices on synchronous generators, used in conjunction with their excitation systems to provide control signals toward enhancing the system damping and extending power transfer limits.

Over the years, a number of techniques have been developed for designing PSSs and other intelligent controllers which are designed with intelligent methods such as fuzzy logic controllers (Fraile-Ardanuy and Zufurua, 2007) and artificial neural network controllers (Segal *et al*., 2004) Also there is other new method to optimize the parameters of PSS such as Genetic Algorithm (GA) and Anti Colony (AC) and particle swarm optimization (PSO). The earlier stabilizer designs were based on concepts derived from classical control theory (Bollinger *et al*., 1975; Tse and Tso, 1988) Many such designs have been physically realized and widely used in actual systems. These controllers feedback suitably phase compensated signals derived from the power, speed and frequency of the operating generator either alone or in various combination as input signals so as to generate an additional rotor torque to damp out the low frequency oscillations. The Gain and required phase lead/lag of the stabilizers are `tuned' by using appropriate mathematical models, supplemented by a good understanding of the system operation. The principles of operation of these controllers are based on the concepts of damping and synchronizing torques within the generator. A comprehensive analysis of these torques has been dealt with by deMello and Concordia in their landmark paper in 1969 [Baster and Schaefer. 2008]. These controllers have been known to work quite well in the field and are extremely simple to implement. However, the tuning of these compensators continues to be a formidable task especially in large multi-machine systems with multiple oscillatory modes. Also there is some information about this issue by Larsen and Swann (1981) which describes in detail the general tuning procedure for this type of stabilizers. PSS design using this method involves some amount of trial and error and experience on part of the designer. Further these controllers are tuned for particular operating conditions and with change in operating conditions they require re-tuning. There for these problems of classical method and bulky equation of this method in power system model leads to use new methods.

On the other hand, Genetic Algorithm is one of the most important intelligent methods for tuning the stabilizer parameters (Grefensteete, 1986) Whereas this method is tested in two case studies in this paper. In continue, we can see the concept of Genetic Algorithm and the effect of this method in two case studies.

II. GENETIC OPTIMIZATION ALGORITHM

In contrast, application of GA in power system stabilizer design is an attractive proposition as it provides greater flexibility regarding controller structure and objective function. In addition to the constraints on the parameter bounds, the GA based optimization problem can readily accomplish control performance constraints, such as required closed-loop minimum performance (Holland, 1975; Davis, 1987) Furthermore, GA helps to obtain an optimal tuning for all PSS parameters simultaneously, which takes care of interactions between different PSSs.

The GA works with a set of individuals comprising the population. The initial population consists of N randomly generated individuals where, N is the size of population. At every iteration of the algorithm, the fitness of each individual in the current population is computed. The population is then transformed in stages to yield a new current population for the next iteration (Mitchell, 2002; Beasley *et al*., 1993). The transformation is usually done in three stages by sequentially applying the following genetic operators:
(1) Selection: In the first stage, the selection operator is applied as many times as there are individuals in the population. In this stage every individual is replicated with a probability proportional to its relative fitness in the population. The population of N replicated individuals' replaces the original population.
(2) Crossover: In the next stage, the crossover operator is applied with a probability pc, independent of the individuals to which it is applied. Two individuals (parents) are chosen and combined to produce two new individuals (offspring). The combination is done by choosing at random a cutting point at which each of the parents is divided into two parts; these are exchanged to form the two offspring which replace their parents in the population. This is known as single point crossover.
(3) Mutation: In the final stage, the mutation operator changes the values in a randomly chosen location on an individual with a probability pm.
Convergence
If the GA has been correctly implemented, the population will evolve over successive generations so that the fitness of the best and the average individual in each generation increases towards the global optimum. The algorithm converges after a fixed number of iterations and the best individual generated during the run is taken as the solution.

The implementation of the simple genetic algorithm is as follows
1- Input:
l: length of each solution string
N: population size, number of strings in a population
pc: probability of crossover
pm: probability of mutation
MAXGEN: maximum number of generations
2- Output:
X*: best string from the current population

Algorithm:

1. Generate N strings, each of length l, randomly to form the initial population.
2. Evaluate each string in the current population and assign a fitness value to each string.
3. Select a highly fit string using selection operator and repeat this process N time to generate a new population of N strings for next generation.
4. Randomly choose pairs of these selected strings and perform crossover with a probability pc to generate children strings. Crossover exchanges bit values between the two strings at one or more locations.
5. Randomly choose some bit positions with a probability pm and mutate the bit values. That is change 1 to a 0 and 0 to a 1.
6. Steps 2-5 constitute a generation. Repeat steps 2-5 till the number of generations is MAXGEN and stop. Output the best string from the current population, which is shown in Fig 1.

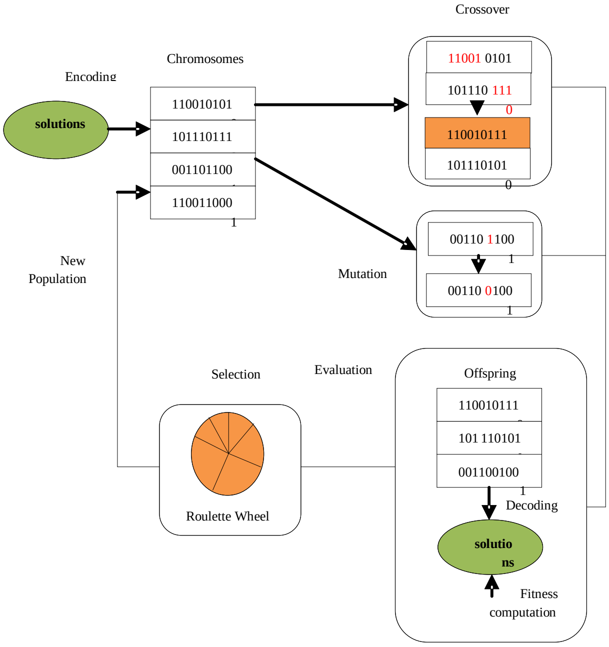

Fig. 1. The general structure of GA

III. PROBLEM STATEMENT

III.I. Power system model

The complex nonlinear model related to an n–machine interconnected power system, can be described by a set of differential- algebraic equations by assembling the models for each generator, load, and other devices such as controls in the system, and connecting them appropriately via the network algebraic equations. Generator in power system is represented by 3 degree of machine model and the problem is to design the parameters of the power system stabilizers (Yu, 1983) For a given operating condition, a multi-machine power system is linearized around the operating point. In this study, the fourth order model (Kundur, 1994) given in Appendix A is used for time domain simulations.

III.II. PSS structure

For simplicity a conventional PSS is modeled by two identical stages, lead/lag network which is represented by a gain KS and four time constants T1, T2, T3 and T4. This network is connected with a washout circuit of a time constant TW, (IEEE, 1992; Abdel-Magid *et al.*, 1990) as shown Fig 3. The operating function of a PSS is to produce a proper torque on the rotor of the machine involved in such a way that the phase lag between the exciter input and the machine electrical torque is compensated. The supplementary stabilizing signal considered is one proportional to the speed (Anderson and Fouad, 1977). A widely speed based used conventional PSS is considered throughout the study (Mishra *et a*l., 2007; Padiyar, 2002). Also, Δωi is the output of this system and is optimized with Genetic Algorithm. Δωi is speed deviation from the synchronous speed. This type of stabilizer consists of a washout filter, as well as a dynamic compensator. The output signal is fed as a supplementary input signal, Vs to the regulator of the excitation system. The washout filter, which essentially is a high pass filter, is used to reset the steady-state offset in the output of the PSS. The value of the time constant Tw is usually not critical and it can range from 0.5 to 20 second.

In this study, it is fixed to 10 sec. The dynamic compensator is made up of two lead-lag stages and an additional gain. The adjustable PSS parameters are gain of the PSS, Ki, and time constants, T1i-T4i. The lead-lag block presence in the system provides phase lead compensation for the phase lag that is introduced in the circuit between the exciter input and electrical torque. In this system, measurement delay, as well as filter and limiter blocks have been used which resulted one added gain block to the system. Moreover, unlike (Mishra *et a*l., 2007; Padiyar, 2002), all PSS parameters were considered adjustable. In addition to fitness of power system this study aims to optimize system's output with these parameters constraints:

$$\textit{Minimize } f \textit{ subject to}: \quad \begin{aligned} K_i^{\min} &\le K_i \le K_i^{\max} \\ T_{1i}^{\min} &\le T_{1i} \le T_{1i}^{\max} \\ T_{3i}^{\min} &\le T_{3i} \le T_{3i}^{\max} \end{aligned}$$

III.III. PSS design using GA

The proposed method was applied for PSSs design in a 3-machine and 9-bus power system model. Single line diagram of the system is shown in Fig 4. Each machine was considered to be equipped with an AVR and PSS. Also, the proposed method was applied for PSSs design in a 10-machine and 39-bus power system called New England model. Single line diagram of the system is shown in Fig 8. For optimization problem, two over mentioned case studies are considered. In both of them objective functions are defined as follows:

$$f = \sum_{i=1}^{ng} (Slip_i - gen)$$

Where,
ng is the number of generators.

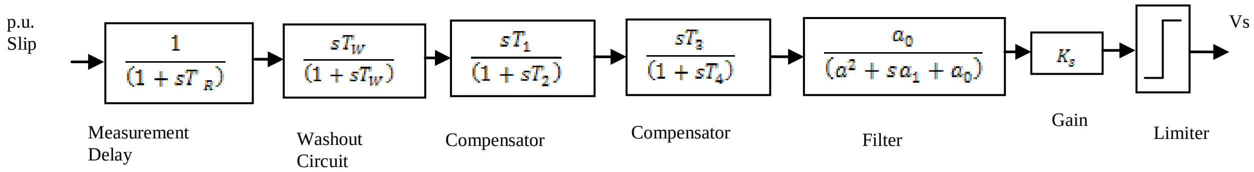

Fig. 2. The Block Diagram of PSS

IV. CASE STUDY 1

In this case, a three-machine nine-bus power system shown in Fig. 4 is considered. Details of the system data are given in Ref. (Larsen and Swann, 1981) To assess the effectiveness and robustness of the proposed method over a wide range of loading conditions, three different cases designated as nominal, light and heavy load. In this case, a three-machine nine-bus power system shown in Fig. 4 is considered. Details of the system data are given in Ref. (Larsen and Swann, 1981). To assess the effectiveness and robustness of the proposed method over a wide range of loading conditions, three different cases designated as nominal, light and heavy load.

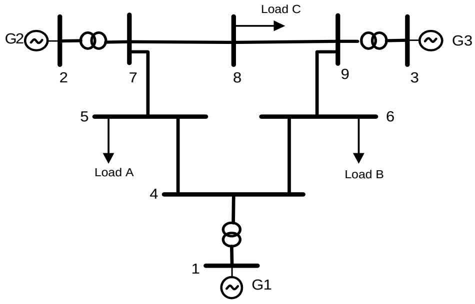

Fig. 4: Three-machine nine-bus power system.

IV.I. GA-based PSS design

In this case, PSS according to the participation factor as given in Ref. (Mishra *et a*l., 2007) is connected to G2 and G3 machines in the test system. PSS parameters must be tuned, optimally to improve the overall system dynamic stability in a robust way under different operating conditions and disturbances.

Results of the PSS parameter set values for the proposed fitness function are given in Table 1. In order to facilitate comparison with GA and conventional approach, design and tuning of the PSS parameters for this multi-machine power system were used (Abido, 2000).

TABLE.1. OPTIMAL VALUES OF GA METHOD IN 3-MACHINE 9-BUSES POWER SYSTEM

Gen	k	T1	T3
G2	1.9365	0.6974	0.8265
G3	**5.0010**	**0.5361**	**0.5039**

In PSS parameters calculation using GA, the crossover and mutation probabilities are selected as 0.5 and 0.08, respectively. The number of individuals in each generation is selected to be 100. Also, Fig.5 shows the optimal trend of fitness functions using GA.

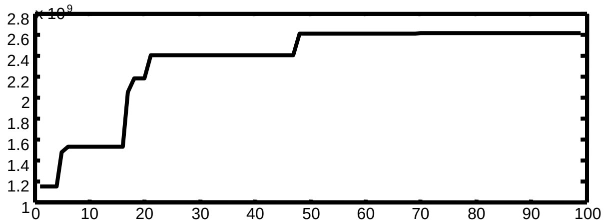

Fig.5: Optimal trend of fitness functions using GA

When PSS is not installed, it can be seen that some of the modes are poorly damped and in some cases, are unstable.

IV.II. Nonlinear time-domain simulation

To assess the effectiveness and robustness of the proposed controller, simulation studies are carried out for the various fault disturbances and fault clearing sequences for two scenarios. Moreover, operation conditions of system and load data are given in Ref.

Scenario 1

It is very important to test the PSS under the loading power factor operating condition. A 0.2 p.u step increase in mechanical torque was applied at t=1.0. Simulation results are shown in Fig 6. It can be seen that the PSS tuned using Genetic Algorithm achieves good robust performance and provides superior. When PSS is not installed, it can be seen that some of the modes are poorly damped and in some cases, are unstable.

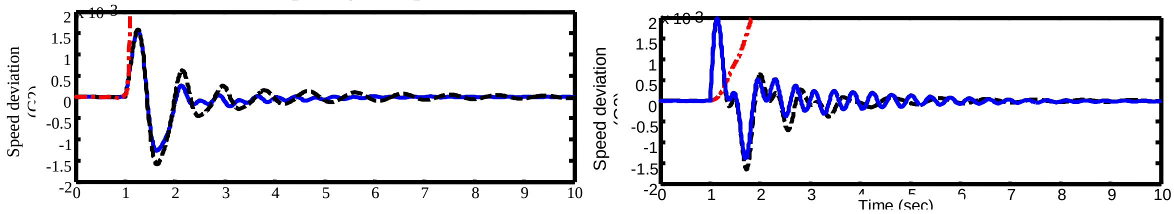

Fig 6: system response to 0.2 p.u. step of torque in scenario 1 for nominal and heavy respectively: Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

- Scenario 2

In this scenario, performance of the proposed controller under transient conditions is verified by applying a 6-cycle three-phase fault at t=1 sec, on bus 7 at the end of line 5-7 Anderson and Fouad, 1977). The fault is cleared by permanent tripping the faulted line. Speed deviations of the generators G2 and G3 under the nominal loading conditions are shown in Fig.7. It can be seen that the PSSs tuned using Genetic Algorithm achieves good robust performance and provides superior damping.

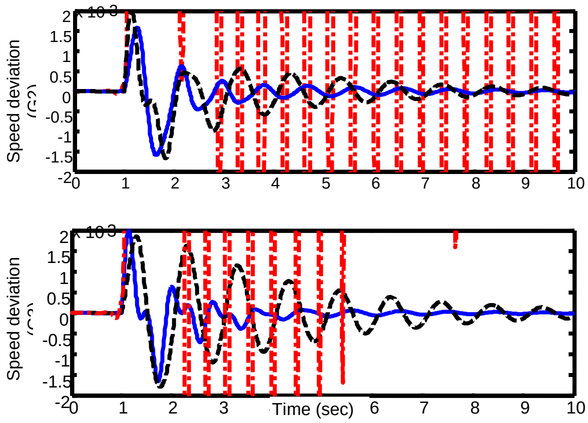

Fig.7: System response under nominal and light loading respectively in scenario 2 for three-phase fault Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

V. CASE STUDY 2

In this case, a ten-machine thirty nine-bus power system (New England) shown in Fig. 8 is considered.

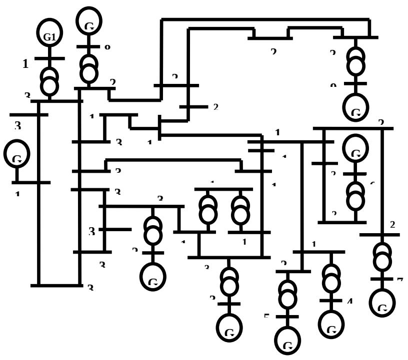

Fig.8: Ten-machine thirty nine-bus New England system.

V.I. GA-based PSS design

In this case, PSS according to the participation factor as given in Ref. (Abdel-Magid *et a*l., 1999) is connected to G2 till G10 machines in the test system. PSS parameters must be tuned optimally to improve the overall system dynamic stability, in a robust way under different operating conditions and disturbances. Results of the PSS parameter set values the proposed fitness function is given in Table 2. In order to facilitate comparison between GA and conventional approach, the design and tuning of PSS parameters for this multi-machine power system were used like (Larsen and Swann, 1981).. In PSS parameters calculation using GA, the crossover and mutation probabilities are selected to be 0.5 and 0.08, respectively. The number of individuals in each generation is selected to be 50. Fig.9 shows the optimal trend fitness functions evaluating process using GA method.

TABLE.2. OPTIMAL VALUES OF GA METHOD IN 10-MACHINE 39-BUS POWER SYSTEM

Gen	k	T1	T3
G2	11.8720	0.1300	0.1300
G3	7.0655	0.2591	0.0010
G4	0.3236	0.0655	0.0978
G5	18.9687	0.8397	0.1300
G6	0.3236	0.5171	0.4204
G7	4.6139	0.3881	0.0978
G8	2.3881	0.0655	0.5816
G9	12.4849	0.6462	0.2591
G10	3.9687	0.0655	0.3881

V.II. Nonlinear time-domain simulation

To assess the effectiveness and robustness of the proposed controller, simulation studies are carried out for the various fault disturbances and fault clearing sequences for two scenarios.

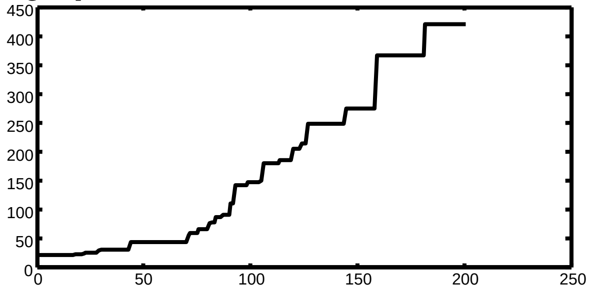

Fig.9: Optimal trend fitness functions using GA

- ***Scenario 1***

In this scenario, it is very important to test the PSS under the loading power factor operating condition. Therefore same as the previous scenario a 0.2 p.u. step increase in mechanical torque was applied at t=1.0. Simulation results are shown in Figs 10-12. It can be seen that PSS tuned using Genetic Algorithm achieves good robust performance and provides superior damping.

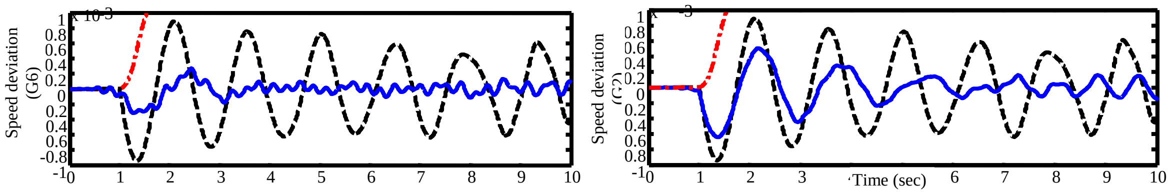

Fig.10: System response to 0.2 p.u. step of torque in scenario 1 for nominal condition Solid (GPSS), Dashed

(CPSS) and Dash-dotted (No PSS)

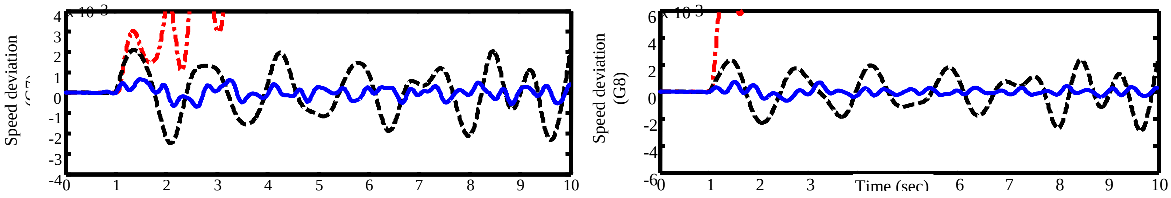

Fig.11: System response to 0.2 p.u. step of torque in scenario 1 for light condition Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

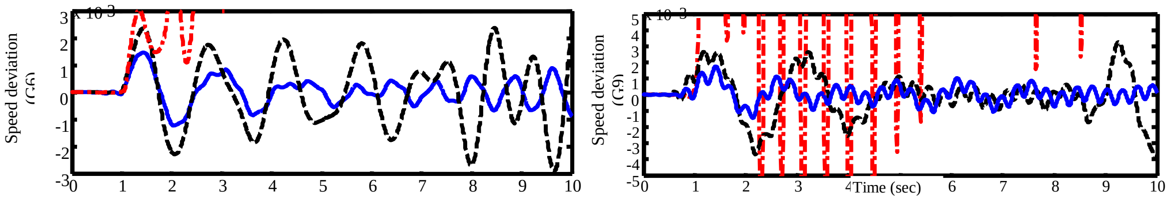

Fig.12: System response to 0.2 p.u. step of torque in scenario 1 for heavy condition Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

- ***Scenario 2***

In this scenario, the performance of the proposed controller under transient conditions is verified by applying a 6-cycle three-phase fault at t=1 sec, on bus 25 at the end of line 25-26 is considered in (Anderson and Fouad, 1977). The simulation results are shown in Figs 13-15. The fault is cleared by permanent tripping of the faulted line it can be seen that the PSSs tuned using the Genetic Algorithm achieves good robust performance and provides superior damping in comparison.

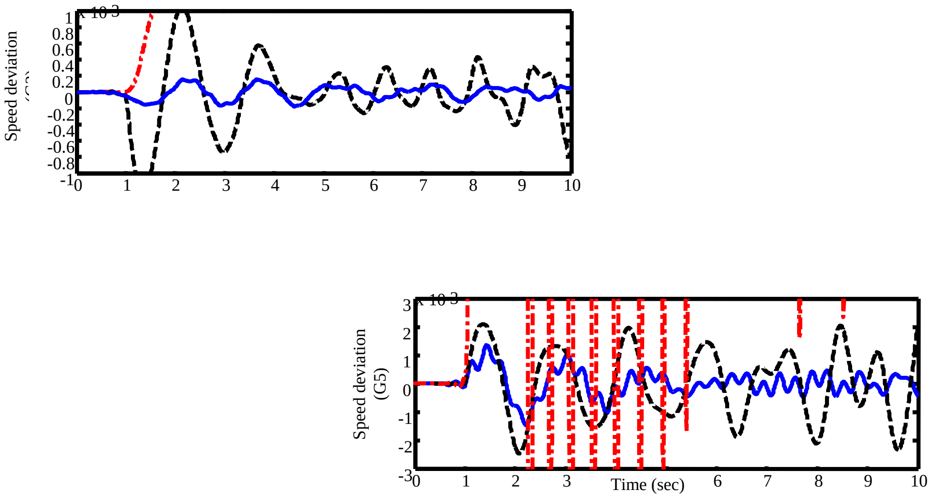

Fig.13: System response under nominal loading in scenario 2 in three-phase fault Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

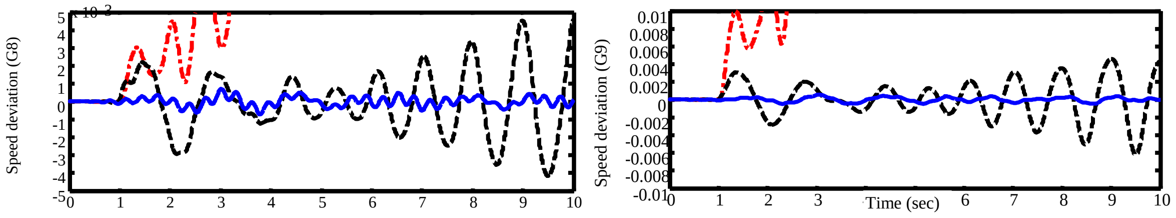

Fig.14: System response under light loading in scenario 2 in three-phase fault Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

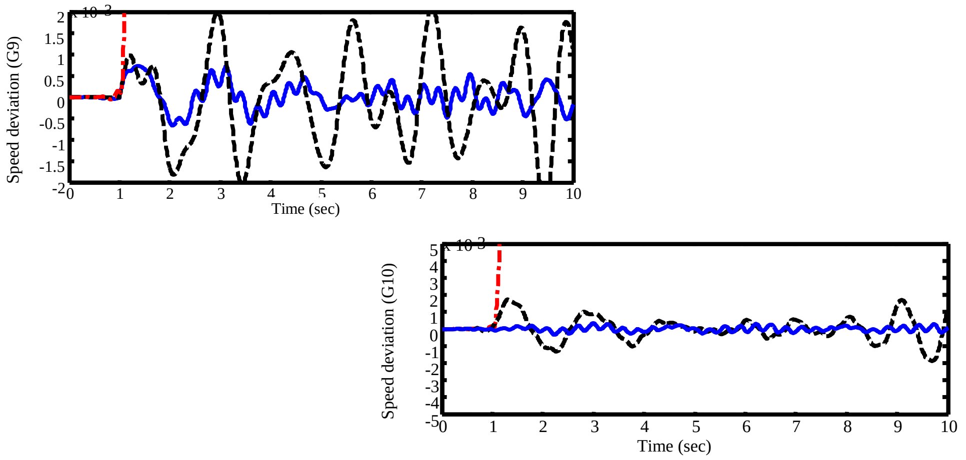

Fig.15: System response under heavy loading in scenario 2 in three-phase fault Solid (GPSS), Dashed (CPSS) and Dash-dotted (No PSS)

- ***VI. CONCLUSIONS***

A new PSO based multi-stage fuzzy controller is proposed for solution of the LFC problem in a restructured power system in this paper. This control strategy was chosen because of increasing the complexity and changing structure of power systems. The effectiveness of the proposed method is tested on a two cases study of power system for a wide range of load demands and disturbances under different operating conditions. All results presented in this paper approves that Genetic Algorithm in multi-machine power system could optimize the parameters of power system stabilizer. Also, new parameters value show that they are appropriate values for achieving system stability, where classical values particularly in New England system could not guarantee a stable the power system.

APPENDIX A Machine models:

$$\dot{\delta}_i = \omega_b(\omega_i - 1)$$

$$\dot{\omega}_i = \frac{1}{M_i}(P_{mi} - P_{ei} - D_i(\omega_i - 1))$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}}(E_{fdi} - (x_{di} - x'_{di})i_{di} - E'_{qi}) \quad \dot{E}_{fdi} = \frac{1}{T_{Ai}}(K_{Ai}(v_{refi} - v_i + u_i) - E_{fdi}) \quad T_{ei} = E'_{qi}i_{qi} - (x_{qi} - x'_{di})\,i_{di}\,i_{qi}$$

NOMENCLATURE

δ Rotor angle of synchronous generator in radians
ωB Rotor speed deviation in rad/sec
Sm Generator slip in p.u.
Smo Initial operating slip in p.u.
H Inertia constant
D Damping coefficient
Tm Mechanical power input in p.u.
Te Electrical power output in p.u.
Efd Excitation system voltage in p.u.
Tdo′ Open circuit d-axis time constant in sec
Tqo′ Open circuit q-axis time constant in sec
Xd d-axis synchronous reactance in p.u.
Xd′ d-axis transient reactance in p.u.
Xq q-axis synchronous reactance in p.u.
Xq′q-axis transient reactance in p.u.
Xc Nominal reactance of the fixed capacitor Xp Inductive reactance of inductor L connected in parallel with C.
k Compensation ratio, k = Xc/Xp
Vt Generator terminal voltage
Eb Infinite-bus voltage
Vs Stabilizing signal from power system stabilizer
TW Washout time constant

REFERENCES

Abdel-Magid Y.L., Abido M.A., AI-Baiyat S. and Mantawy A.H. (1999). "Simultaneous Stabilization of Multi-machine Power Systems Via Genetic Algorithms", *IEEE Trans. Power Syst.* 4(4): 1428–1439.

Abido M.A. (2000). "Robust Design of Multi-machine Power System Stabilizer Using Simulated Annealing", IEEE Trans. *Power Syst.* 15(3): 297 – 304.

Anderson PM., Fouad AA (1977)." Power System Control and Stability", Ames, IA: Iowa State University Press, Vol. 17.

Basler M.J. and Schaefer R.C. (2008). "Understanding Power System Stability", IEEE Trans. Industry Applications, 2008, Vol. 44, pp. 463-474

Beasley D., Bull D.R., andMartin R.R. (1993) "An Overview of Genetic Algorithms: Part 1, Fundamentals", University Computing. 5(2):58-69.

Bollinger K., Laha A., Hamilton R. and Harras T. (1975). "Power System Stabilizer Design Using Root-Locus Methods", IEEE Transaction on PAS. 94(5): 1484-1488.

Davis L (1987). "Genetic Algorithms and Simulated Annealing", Pitman..

Fraile-Ardanuy J. and Zufiria P.J. (2007). "Design and Comparison of Adaptive Power System Stabilizers Based on Neural Fuzzy Networks and Genetic Algorithms", Neuro computing. 70: 2902-2912.

Grefenstette J.J. (1986). "Optimization of Control Parameters for Genetic Algorithms", *IEEE Trans. Syst., Man, Cybern*, 16:122–128.

Holland H. (1975)."Adaptation in Natural and Artificial Systems", MIT Press.

IEEE, (1992). Recommended Practice for Excitation Systems Model for Power System Stability Studies, *IEEE Standard.* 421.5-1992.

Klofenstein A (1971). Experience with System Stabilizing Excitation Controls on the Generation of the Southern California Edition Company", *IEEE Transactions on PAS*. 90(2): 698-706.

Kundur P. (1994)." Power System Stability and Control", McGraw-Hill Inc., New York, 1994.

Larsen E. and Swann D. (1981). Applying Power System Stabilizers", IEEE Trans. Power App. Syst., 1981, Vol. 100, No. 6, pp. 3017-3046, 1981.

Larsen R.V. Swann D.A. (1981). Applying Power System Stabilizers, I, II and III", *IEEE Transactions on PAS,* 100(6): 3017-3046.
Mishra S., Tripathy M. and Nanda J. (2007). "Multi-machine Power System Stabilizer Design by Rule Based Bacteria Foraging", *Elec. Power Syst.* 77: 1595-1607
Mitchell M (2002). "An Introduction to Genetic Algorithms", Prentice Hall, India.
Padiyar KR (2002)" Power System Dynamics-Stability and Control", BS Publications, Hyderabad, India, Vol. 24.
Segal R., Sharma A. and Kothari M.L. (2004). "A Self-tuning Power System Stabilizer Based on Artificial Neural Network", Vol. 26, pp. 423-430.
Tse C.T. and Tso S.K. (1988). "Approach to the Study of Small-perturbation Stability of Multi-machine Systems ", IEE Proceedings, Generation. Transmission Distribution. 135(5): 396-405.
Yu N. (1983). Electric Power System Dynamics", Academic Press, 1983.

