

Design of A Self-Tuning Adaptive Power System Stabilizer

R. Ajabi-Farshbaf¹, M. Tarafdar-Hagh², A. Roshan-Milani³

¹Tabriz Electric Distribution Company, Tabriz, Iran
Email: r_ajabi@sut.ac.ir (Corresponding author)

²Faculty of Electrical & Computer Engineering, University of Tabriz, Tabriz, Iran
Email: tarafdar@tabrizu.ac.ir

³Tabriz Electric Distribution Company, Tabriz, Iran

ABSTRACT

Power system stabilizers (PSSs) must be capable of providing appropriate stabilization signals over a broad range of operating conditions and disturbances. The main idea of this paper is changing a classic PSS (CPSS) to an adaptive PSS using genetic algorithm. This new genetic algorithm based on adaptive PSS (GAPSS) improves power system damping, considerably. The controller design issue is formulated as an optimization problem that is solved by GA to identify PSS parameters in various operating conditions. Numerical simulation studies have been done on a modified model of IEEE second benchmark. The consequence of these studies shows that, the performance of the suggested genetic algorithm based adaptive PSS in damping of electromechanical oscillations of power system is better than CPSS.

KEYWORDS: Power System Stabilizer, Genetic Algorithm, Adaptive Controller, Electromechanical Oscillations

1. INTRODUCTION

A CPSS is a controller with fixed parameters usually designed using linear and classic control techniques. Because of its fix parameters, they are not suitable for a wide range of operating conditions [1]. On the other hand, in many traditional power systems, also some new established power plants, CPSSs are widely used. To reduce the mentioned drawbacks of the CPSS, it may be supplanted by new PSSs based on advanced control techniques. The main idea of this replacement is to increase the loadability of power transmission system. However, the damping rate of oscillations is

still an important issue [2], [3]. Unfortunately, replacing the CPSS by PSSs based on new methods needs replacement of the whole control algorithm, structure and implementation method. Therefore, it is necessary to obtain a method with a little change.

By using necessary power system parameters, it is possible to access on-line determination of CPSS parameters in such a way that it can stabilize the power system oscillations more efficiently. Indeed, by proposed method, it is not necessary to replace the existing CPSS with other adaptive PSS it is sufficient to determine

the optimum values of CPSS parameters. The most commonly used identifiers are based on the Root Least Squares (RLS-Identifiers) and Neural Networks (NN). The major drawback of RLS-Identifiers are ‘blow up’ of the covariance matrix. On the other hand, the eminent drawback of NN based techniques is their ‘black-box’ description [4]. In the last few years, optimizing search techniques are progressively being applied to power system controllers. This tendency has been prompted by expansion of powerful computational platforms and high speed computer systems. Among these numerical techniques, especially those with evolutionary algorithms, genetic algorithm (GA) is one of the most appealing one, in many fields such as identification methods and engineering optimal design [5].

In this paper, a constructive application of GA with a novel adaptive scheme for identification of power system parameters is presented. Then, the results are used for optimum tuning of CPSS parameters. This new PSS is called GAPSS and its operation is compared to CPSS results. The paper is organized as follows: section 2 deals with a general overview of GA. Section 3 contains descriptions of the modeling of case study power systems. Formulation and structure of proposed GAPSS are explained in section 4. Section 5 includes the simulation results. Section 6 presents the conclusions of this paper.

2. OVERVIEW OF GENETIC ALGORITHM

A genetic algorithm is a stochastic search algorithm that uses models based on natural biological evolution. GA is known as a probabilistic optimization method and classified as the most recent and powerful

computational products of the artificial intelligence (AI) technique [5]. Genetic algorithms operate on a population of potential solutions applying the principle of survival of the fittest to produce better and better conjectures to a solution. Prior to use of GA, a fitness function and desirable conditions must be defined. At each generation, a new set of conjectures is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. Evolutionary algorithms model natural processes such as selection, recombination, mutation and replacement. Although GA provides a powerful adaptive search mechanism, but it has a few of drawbacks that some of them are highlighted in [6].

First, optimal performance of GA depends on the optimal selection of its operators such as population size, mutation probability, the number of repetition and rate of crossover. Particularly these parameters interact with one another in a nonlinear manner that make the optimization procedure difficult to do. Thus, these parameters must be optimized before use of GA. This is usually done by trial and error. Second, there is a high probability that the population will converge to very similar solution vectors as the search progresses. This problem is said “genetic drift” that prevents GA from maintaining diversity in its population [6]. It is possible once the population has converged, the crossover and mutation operators become ineffective in exploring new portions of the function space. Third, another problem closely related to “genetic drift” is premature convergence and the trap to local minima. This problem prevents

GAs from converging to the “global optimum”.

Overcoming the mentioned restrictions, three main operators are used in this paper: probably factor, learning rate and forgetting factor. The probability vector controls the random bit strings. The individuals are evaluated according to the objective function. The “best” individual is used to update the probability vector so as to produce solutions to the current best individuals through learning. Therefore, there is no need to store all solutions in the population. A slightly different mutation operator is used, that is a forgetting factor to relax the probability vector toward neutral value of 0.5. Several methods can be used to perform mutation. A mutation on the probability vector is performed on the proposed method. As mentioned, there are several drawbacks for GA and suggested solutions must be performed in computer programming of GA that makes GA faster than previous. In this work the drawbacks of GA, as outlined above, have been considered. A summary of the GA procedure applied in this paper is given in appendix A. Because of a considerable number of power system GA-related works; we haven't included a detailed information about GA. Almost a complete list of papers treating the issue of GA applications in power systems is presented in reference [7].

3. POWER SYSTEM MODEL

The simulations are performed on a modified IEEE second benchmark model that is illustrated in figure 1. In this figure, there are a synchronous generator unit, transformer and a transmission system with two lines that is connected to infinite bus. The block diagram of the generator plant model is shown in figure 2. It includes a

first order AVR model, an exciter model that feeds the synchronous generator field winding, a PSS model that provides an additional input signal to damp low frequency oscillation and Heffron-Philips linearized model of generator [1]. Electromechanical oscillations are generally studied by analysis of a linearized model. There are two major loops in figure 2, the mechanical loop on top and an electrical loop at bottom. The mechanical loop consists of two transfer function blocks. The left one is based on the equation of the torque equilibrium while the right one is the relationship between the angle and speed of the unit. In these blocks J , D and ω_0 stand for the inertia constant, the mechanical damping coefficient and the synchronous speed, respectively. There is a reference control voltage v_r minus the incremental terminal voltage Δv_t as the input and incremental internal voltage $\Delta e'_q$ as the output of electrical loop. ΔT_e and ΔT_m are the electric torque and mechanical torque, respectively. Δv_t consists of $K_5 \Delta \delta$ due to torque angle variation and $K_6 \Delta e'_q$ due to $\Delta e'_q$ variation. The right block of an electrical loop represents an exciter and AVR with a time constant T_A and an overall gain K_A . This block should be expanded when the system has rotating exciter and AVR. The left block represents the field current transfer function as affected by the armature reaction, with a time constant $K_3 T'_{d0}$ and a gain K_3 .

Currently, most generators are equipped with automatic voltage regulators (AVR) to automatically control the terminal voltage. It is well known that the voltage regulator action has a detrimental impact upon the

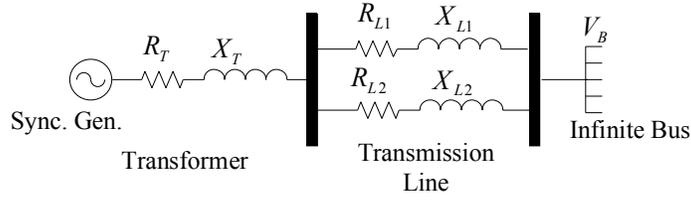


Fig. 1. Modified diagram of IEEE second benchmark model.

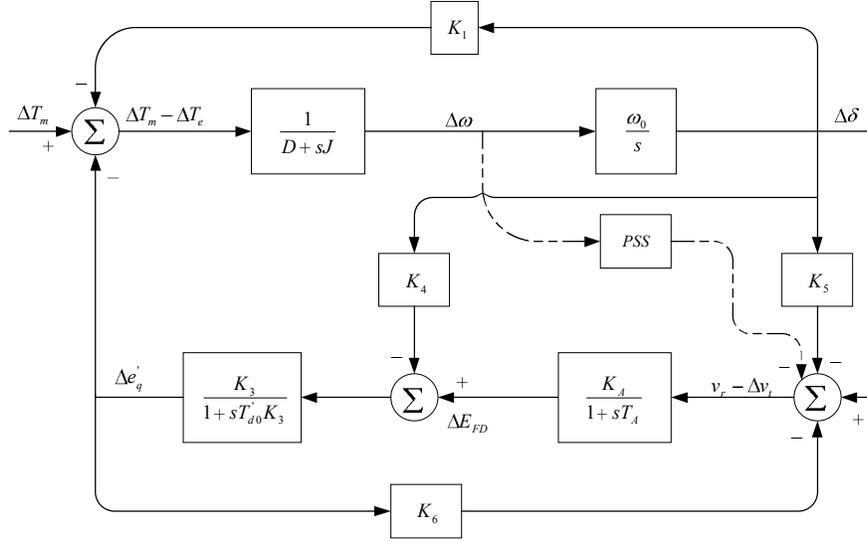


Fig. 2. Heffron-Philips linearized block diagram of generator plant.

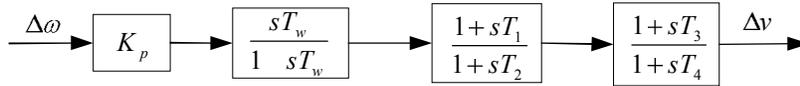


Fig. 3. A model of CPSS.

dynamic stability of the power system [8].

As illustrated in figure 2, the stabilizing signal is introduced in conjunction with the reference voltage to the regulator and exciter system. A CPSS detailed model is shown in figure 3 and its transfer function is given by (1) as follows:

$$TF(s) = K_p \cdot \frac{sT_w}{1+sT_w} \cdot \left(\frac{1+sT_1}{1+sT_2} \right)^k \cdot \left(\frac{1+sT_3}{1+sT_4} \right)^k \quad (1)$$

The first term in (1) is a reset term that is used to “washout” the compensation effect after a time lag T_w . The use of reset control will assure no permanent offset in the

terminal voltage due to a prolonged error in frequency, which may occur in an overload or islanding condition [2]. The T_w is big enough so it will not disturb the operation of main compensator. The second and third terms of (1) are lead compensators to account for the phase lag through the electrical system. In many practical cases, the required phase lead is greater than that is obtainable by a single lead network. In this case, cascaded lead stages are used where k is the number of lead stages. The numerical values of plant and line

parameters that are used in simulations are as below:

J	Moment of inertia of rotating system of generating unit	9.26 kgm^2
D	Mechanical damping coefficient	0 $N.m.s$
T'_{d0}	Armature reaction time constant	7 sec.
E'_q	Internal voltage of field winding	2.365 p.u.
K_A	Overall gain of exciter and AVR	10
T_A	Overall time constant of exciter and AVR	0 sec.
x_d	Synchronous reactance in d-axis	0.97 p.u.
x'_d	Transient reactance in d-axis	0.19 p.u.
x_q	Synchronous reactance in q-axis	0.96 p.u.
R_T	Overall resistance of source and transformer	0.003 p.u.
X_T	Transformer reactance	0.15 p.u.
X_{L1}	Reactance of line 1	1 p.u.
X_{L2}	Reactance of line 2	1 p.u.
R_L	Lines' resistance	0 p.u.
V_B	Infinite bus voltage	0.995 $\angle 0$ p.u.
f	Frequency	50 Hz

The other parameters, K_1, \dots, K_6 , shown in figure 2, can be calculated based on the above parameters that are reviewed in appendix B.

4. PROPOSED METHOD

Adaptive control techniques are very suitable control algorithms for non-linear systems. Self-tuning control (STC) is one of the common methods of adaptive control techniques and it has been used widely in engineering applications [9]. Figure 4 shows a general block diagram of self-tuning adaptive controller. It consists of three major parts: "A model of plant", "a model parameter identification unit" and a "controller". The flowchart of the proposed method is illustrated in figure 5. Compared

with figure 4, the plant model and the model parameter identification unit are illustrated in the dash area. The plant model consists of all components of figure 1 that are described in section 3. The model parameter identification unit that makes decisions of control strategy and GA subroutine is used as a part of this unit. The controller is CPSS in this paper. In almost all adaptive controllers, on-line modification of the controller parameters is done and it needs to on-line measurement of performance indexes and a model of plant [9].

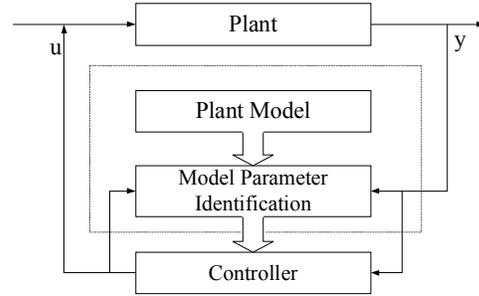


Fig. 4. Self-tuning adaptive controller (STC).

At first step, initial values and control parameters such as the permissible ranges of PSS parameters (i.e. in (2)), generator, AVR, exciter, transformer, infinite bus and transmission lines characteristics must be entered. Since these settings and target data are fixed, they can be stored on a NOVRAM or EEROM and then they can be recalled in each start of the program. In the next step, the on-line measurements must be entered i.e. voltages in generator terminals and buses, currents in transformer and lines, exciter voltage, mechanical torque and frequency. For the first data reception, it is required to run the procedure to optimize and tune PSS parameters. Depending on the system configuration (figures 1 and 2 in this paper that are known as plant model) the network and measured

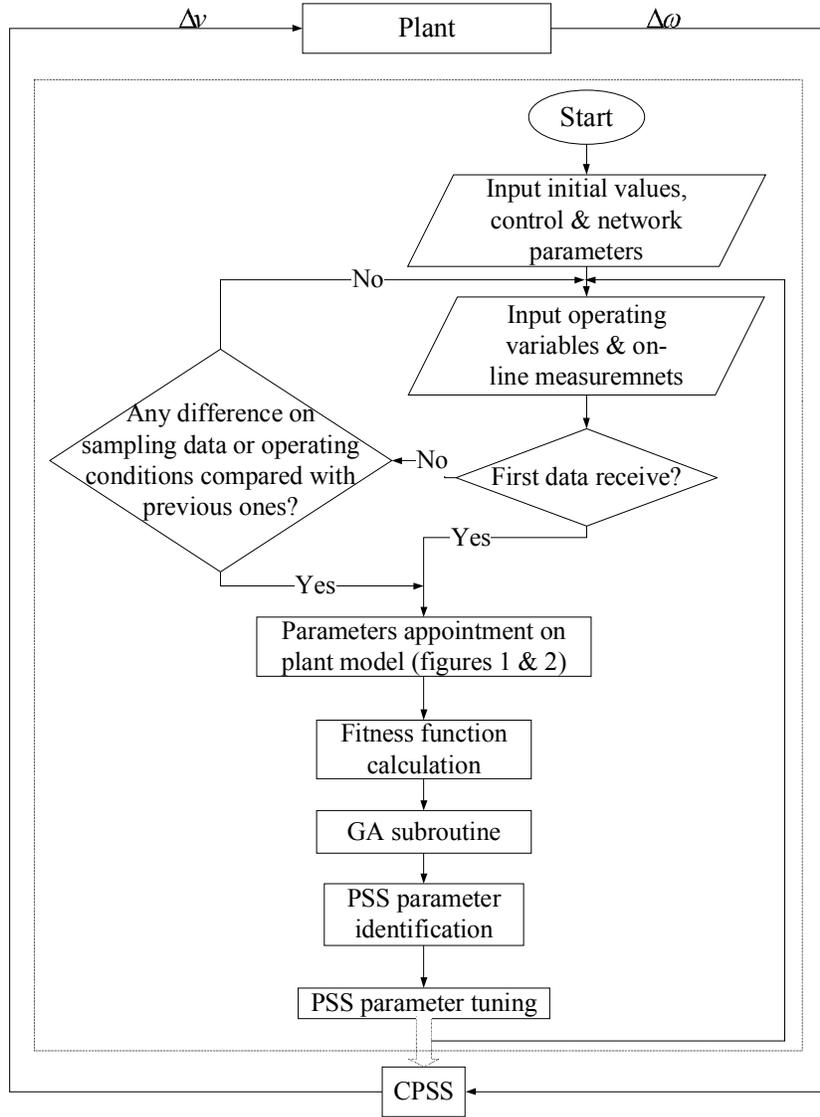


Fig. 5. A flowchart of the proposed method

parameters must be appointed in the plant model. Now, the fitness function can be calculated. The fitness function of the GA is obtained by simplification of the equations that dominate on the power system and are shown in figure 1 and block diagram of figure 2. The simplification is performed using "Mason's signal flow rules" for calculation of $|\Delta\omega/\Delta v_f|$ transfer function [10]. The objective is to optimize the parameters of PSS to maximize the

oscillation damping ratio that means the $|\Delta\omega/\Delta v_f|$ minimization. Then, GA subroutine can be applied to optimize the parameters of CPSS including its gain and time constants of the compensators that convert it to a genetic algorithm based adaptive PSS. Finally, these parameters must be tuned on the PSS. If network conditions and input parameters change, this process will be redone to return PSS parameters for the new state.

When input data vary, due to a change in power system, they will be fed into GA. Then, GA determines the optimum parameters of PSS for new condition. But, if power system has no substantial changes for a time interval, resulting input data be constant, GA won't be fed by them and therefore, GA will have no effect on the PSS. In other words, the dashed section of figure 5 will not influence the PSS and the PSS operates as a CPSS for negligible changes in the power system. It is obvious that the suggested adaptive GAPSS structure has a slight deviation from CPSS structure.

5. SIMULATION RESULTS

Simulation results are obtained using MATLAB software. It is assumed that two lead-lag compensators are sufficient to this task in order to provide a desired damping ratio. The time constant of washout filters of all PSS's are set to two seconds. Considering the model of CPSS in figure 4, there are five parameters of PSS that must be optimized with GA. The permissible ranges of variations of these parameters are considered to be as follows:

$$\begin{cases} 0 \leq k_p \leq 20 \\ 0 \leq T_1, T_3 \leq 1 \\ 0 \leq T_2, T_4 \leq 0.5 \end{cases} \quad (2)$$

Meanwhile, during the simulation, in order to compare the results of both GAPSS and CPSS, the parameters of CPSS are fixed to values shown in table 1.

Table 1.Parameters of CPSS.

k_p	T_1	T_2	T_3	T_4
12	0.8	0.4	0.6	0.2

In this paper, the configuration of GA is as follows: Length of chromosome is 40 bits, initial population is 50, generations are 250, forgetting factor of mutation is 0.005 and learning rate is assumed 0.6. Selection

is based on circular normalized geometric distribution and arithmetic crossover is used. By considering above values the following cases are studied.

Case 1: In this case, step change of mechanical power from 1 p.u. to 1.3 p.u. is evaluated. Active and reactive powers of load at steady state condition are assumed 0.9 p.u. and 0.3 p.u. lag, respectively. By using the GA, the new parameters of PSS are modified as shown in table 2.

Table 2.Parameters of GASS for $P = 0.9, Q = 0.3$ lag, p.u.

k_p	T_1	T_2	T_3	T_4
19.3725	0.898	0.1922	0.9451	0.1235

Figures 6 and 7 illustrate rotor angular speed changes and load angle changes, respectively. In these figures the results are compared with CPSS. It can be seen that GAPSS has suitable response and the damping rate of oscillations is improved.

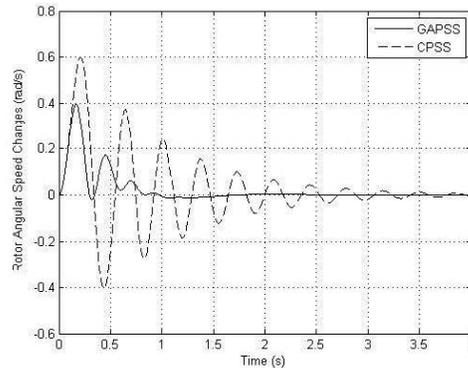


Fig. 6. Rotor angular speed in case 1.

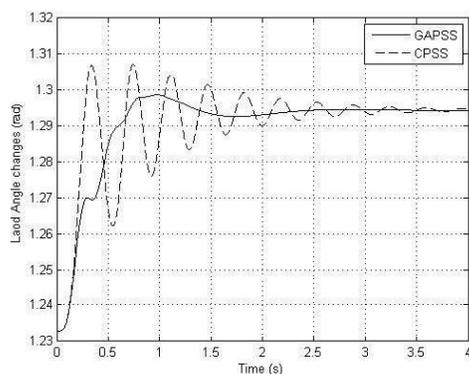


Fig. 7. Load angle change in case 1.

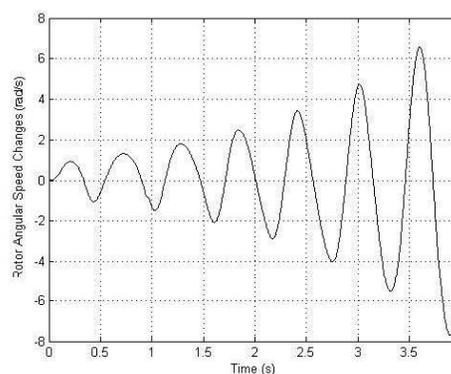


Fig. 8. Rotor angular speed changes in case 2 (the parameters of PSS are not tuned for new condition).

Case 2: In this case, the suggested values of both CPSS and GAPSS in case 1 are used in new conditions such as $P=1.2$ and $Q=0.7$, lag, p.u. The objective of this case is to show that power system will be unstable faced with mechanical torque change of 0.3 per unit. Figure 8, clarifies this instability with a PSS that its parameters mentioned in table 2. The result of CPSS parameters that are mentioned in table 1 has worse performance.

In recent loading condition, GA is applied to power system and its results are shown in table 3. On the other hand, simulations show that power system in this state is stable without any PSS. These two cases are compared in figure 9. It shows that, GAPSS has better result and damp oscillations with higher rates.

Table 3. Parameters of GASS for $P=1.2, Q=0.7$ lag, p.u.

k_p	T_1	T_2	T_3	T_4
4.8235	0.8392	0.0333	0.9961	0.4706

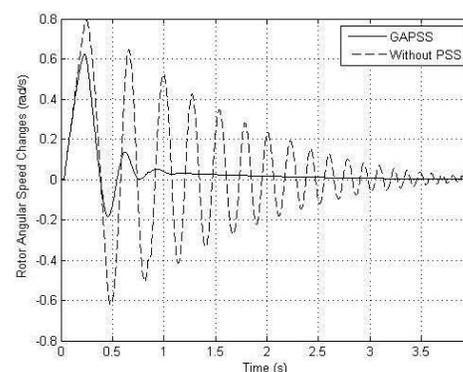


Fig. 9. Rotor angular speed changes in case 2.

The main result of the cases 1 and 2 is that the GAPSS has much better performance than CPSS, but it must be tuned for several operating points to improve and adapt its performance in a broad range of conditions. A self-tuning adaptive scheme is studied in cases 3 and 4.

Case 3: In this case, load stochastically changes will be evaluated. initial condition of load is assumed to be $P=0.9$ and $Q=0.3$, lag, p.u. Then the load changes to $P=0.1$ and $Q=0.1$, lag, p.u.

In this case, it is assumed that GAPSS with new parameters values affects on power system after one second delay. The parameters for this case are shown in table 4. The rotor angular speed changes and load angle changes are shown in figures 10 and

11, respectively and both of them are compared with CPSS performance.

Case 4: Tuning time delay is an important practical aspect that depends on practical limits such as measuring and communications system time delay, uploading system data to CPU, process speed and GAPSS parameters tuning.

In this case, similar to case 1, step change of mechanical power from 1 p.u. to 1.3 p.u. is evaluated. Active and reactive powers of load at steady state condition are assumed 0.9 p.u. and 0.3 p.u. lag, respectively. To study the effect of tuning time delay on the damping ratio, three different tuning times are evaluated. All three GAPSSs applied in this case are tuned to initial conditions (table 2). The first one which is named “GAPSS1” has no change facing load changes. The second and third GAPSS are named “GAPSS2” and “GAPSS3” and their parameters, changes in values mentioned in table 4 after 0.5 and 1 second, respectively. Figures 12 and 13, show rotor angular speed changes and load angle changes respectively in this case. Approximately, GAPSS1, GAPSS2 and GAPSS3 are similar and have better performance than CPSS but comparing with each other GAPSS2 has the best operation. Also, from figures 12 and 13, it can be deduced, that system performance will be better as if the tuning time of GAPSS parameters decreases. It is considerable that, the proposed adaptive GAPSS will act similar to CPSS facing with transient conditions. Consequently, adaptive GAPSS is very suitable facing with all disturbances that occur within a time that is longer than its optimization and tuning time.

k_p	T_1	T_2	T_3	T_4
17.9608	0.9922	0.2725	0.9804	0.0196

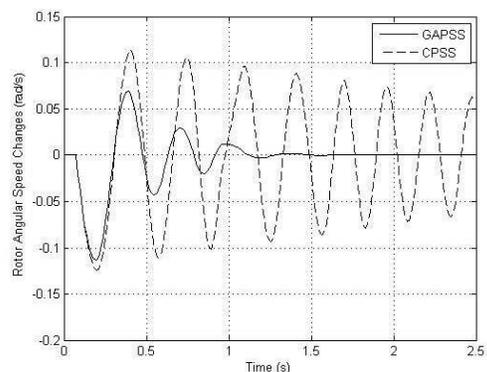


Fig. 10. Rotor angular speed changes in case 3.

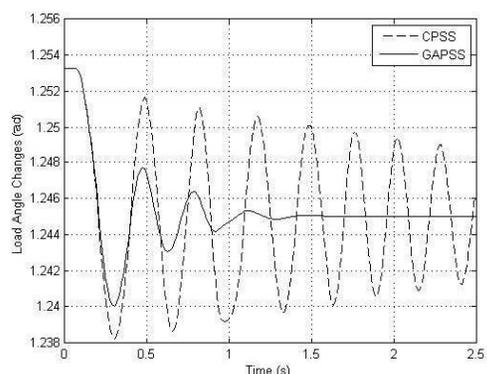


Fig. 11. Load angle changes in case 3.

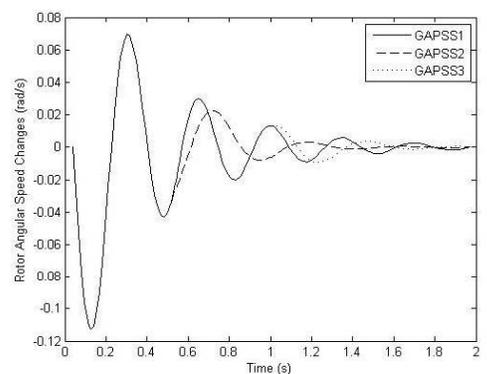


Fig. 12. Rotor angular speed changes in case 4 (for tuning after 0.5 and 1 seconds).

Table 4. Parameters of GASS for $P=0.1, Q=0.1$ lag, p.u.

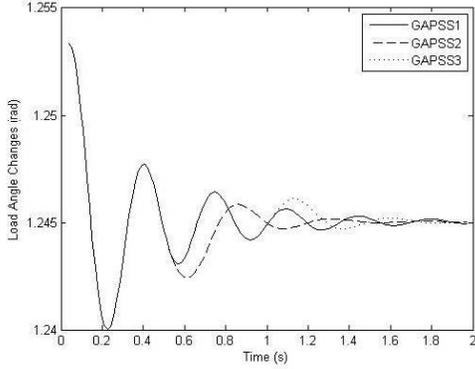


Fig. 13. Load angle changes in case 4 (for tuning after 0.5 and 1 seconds).

6. CONCLUSIONS

This paper presented a genetic algorithm based, adaptive power system stabilizer. By means of proposed method, it is sufficient to add the GA- based identifier to the existing structure of CPSS so, even in the worst case such as failure of GA- based identifier, the GAPSS will operate as a CPSS. Overcoming genetic drift and premature convergence of the GA, probably a factor, learning rate and forgetting factor are used in this paper. Simulation results show that by using GAPSS the rotor angle speed and load angle changes have less settling time for different conditions of power system operation. Also, it has been shown that, without using the proposed GAPSS, power system may be unstable. In addition, compared with CPSS, the proposed GAPSS is more effective and robustness.

APPENDIX A

This appendix contains a review of GA procedure applied in this paper, [6].

Stage 1: Initialize probability vector to 0.5 to ensure uniformly random bit strings.

Stage 2: Perform population generation of uniformly random bit strings and element-by-element comparison with the

probability vector. Wherever an element of probability vector is greater than the corresponding random element “1” is generated, else “0” is generated.

Stage 3: Interpret each bitstring as a solution and evaluate its merit to identify the “best”.

Stage 4: Adjust probability vector to favor the generation of the bitstring.

Stage 5: Generate a new population reflecting the modified distribution.

Stage 6: Stop if a satisfactory solution is found, else go to stage 3.

APPENDIX B

This appendix contains a review of the equations of Heffron-Philips linearized model and the studied power system model, [1], which are used in simulations.

$$y_d = \frac{1}{x'_d} \quad (A1)$$

$$I = \sqrt{\frac{P^2 + Q^2}{V_B^2}} \quad (A2)$$

$$\varphi = \arctan\left(\frac{Q}{P}\right) \quad (A3)$$

$$\delta_0 = \arctan \frac{I \times ((x_q + X_T + X_L) \times \cos \varphi - (r_s + R_L) \times \sin \varphi)}{V_B + I \times ((x_q + X_T + X_L) \times \sin \varphi + (r_s + R_L) \times \cos \varphi)} \quad (A4)$$

$$V_{d0} = V_B \sin \delta_0 \quad (A5)$$

$$V_{q0} = V_B \cos \delta_0 \quad (A6)$$

$$F_d = \frac{V_B \sin \delta_0}{x'_d} \quad (A7)$$

$$F_q = \frac{V_B \cos \delta_0}{x_q} \quad (A8)$$

$$K_1 = \frac{E'_q V_B^2 \cos \delta_0}{x'_d} + V_B^2 \cos(2\delta_0) \left(\frac{1}{x_q} - \frac{1}{x'_d} \right) \quad (A9)$$

$$K_2 = \frac{V_B^2 \sin \delta_0}{x'_d} \quad (A10)$$

$$K_3 = \frac{1}{1 + (x_d - x'_d) y_d} \quad (A11)$$

$$K_4 = F_d (x_d - x'_d) \quad (A12)$$

$$K_5 = -\frac{V_{d0}}{\sqrt{V_{d0}^2 + V_{q0}^2}} F_q x_q + \frac{V_{q0}}{\sqrt{V_{d0}^2 + V_{q0}^2}} F_d (X_T + X_L) \quad (A13)$$

$$K_6 = \frac{V_{q0}}{\sqrt{V_{d0}^2 + V_{q0}^2}} y_d \quad (A14)$$

REFERENCES

- [1] Yao-nan Yu, "Electric Power System Dynamics", *Academic Press*, 1983.
- [2] P.Hoang, K. Tomsovic, "Design and Analysis of an Adaptive Fuzzy Power System Stabilizer", *IEEE Transaction on Energy Conversion*, Vol.11, No.2, Page(s): 455-461, June 1996.
- [3] Abdelazim, Tamer, O. P. Malik, "An Adaptive Power System Stabilizer Using On-Line Self-Learning Fuzzy System", *IEEE Power Engineering Society 2003 General Meeting*, Vol.3, pp:1715-1720, July 2003.
- [4] P. Shamsollahi, O. P. Malik, "An Adaptive Power System Stabilizer Using On-Line Trained Neural Networks", *IEEE Transaction on Energy Conversion*, Vol. 12, Page(s): 382-387, 1997.
- [5] W.Hussein, O.P.Malik, "GA-Identifier and Predictive Controller for Multi-Machine Power System", *Power India Conference, IEEE*, on CD, April 2006.
- [6] K.A. Folly, "Design of Power System Stabilizer: A Comparison between Genetic Algorithms and Population-Based Incremental Learning", *IEEE Power Engineering Society General Meeting, on CD*, June 2006.
- [7] V.Miranda, S.Srinivasan, L.Proenca, "Evolutionary Computation in Power Systems", *International Journal of Electric Power and Energy Systems*, Vol.20, Page(s): 89-98, January 1998.
- [8] E.R.C.Viveros, G.N.Taranto, D.M.Falcao, "Coordinated Tuning of AVRs and PSSs by Multi-Objective Genetic Algorithms", *ISAP 2005*, Page(s): 247-252, 2005.
- [9] K. J. Astrom, B. Wittenmark, "Adaptive Control", *Addison Wesley*, 1989.
- [10] Benjamin C. Kua, "Automatic control systems", *Prentice Hall of India*, 2003.