A GENETIC-BASED FUZZY LOGIC POWER SYSTEM STABILIZER FOR MULTIMACHINE POWER SYSTEMS

M. A. Abido *Y. L. Abdel-Magid*
Electrical Engineering Department
King Fahd University of Petroleum and Minerals
Dhahran 31261, Saudi Arabia

Abstract – This paper presents a novel approach to combine genetic algorithms (GA) with fuzzy logic systems to design a genetic-based fuzzy logic power system stabilizer (GFLPSS) for multimachine power systems. Incorporation of GA in fuzzy logic power system stabilizers (FLPSSs) design will significantly reduce the time consumed in the design process of FLPSSs. It is shown in this paper that the performance of FLPSS can be improved significantly by incorporating a genetic-based learning mechanism. The performance of the proposed GFLPSS under different disturbances is investigated. The results show the superiority of the proposed GFLPSS as compared to the classical PSS and its capability to enhance system damping to local as well as interarea modes of oscillations. The capability of the proposed GFLPSS to work cooperatively with the existing classical PSSs is also demonstrated.

1. INTRODUCTION

Due to increasing complexity of electrical power systems, there has been increasing interest in the stabilization of such systems. In the past two decades, the utilization of supplementary excitation control signals for improving the dynamic stability of power systems and damping out the low frequency oscillations due to disturbances has received much attention [1-9]. Nowadays, the conventional power system stabilizer (CPSS) - a fixed parameters lead-lag compensator - is widely used by power system utilities [3]. The gain settings of these stabilizers are determined based on the linearized model of the power system around a nominal operating point to provide optimal performance at this point. Generally, the power systems are highly nonlinear and the operating conditions can vary over a wide range. Therefore, CPSS performance is degraded whenever the operating point changes from one to another because of fixed parameters of the stabilizer.

Alternative controllers using adaptive control algorithms have been proposed to overcome such problems [5-6]. However, most adaptive controllers are designed on the basis of parameter identification of the system model in real-time which results in time consuming and computational burden.

Recently, fuzzy logic power system stabilizers (FLPSSs) have been proposed [7-9]. FLPSSs appear to be the most suitable stabilizers due to their lower computation burden and robustness. Unlike the most classical methods, an explicit mathematical model of the system is not required to design a good FLPSS which makes it more suitable for on-line computer control. In addition, FLPSS can be easily set up using microcomputer with A/D and D/A converters [10].

Although fuzzy logic controllers showed promising results, they are subjective and somewhat heuristic. In addition, generation of membership functions, and the choice of scaling factors are done either iteratively, by trial-and-error, or by human experts. There is to-date no generalized method for the formulation of fuzzy control strategies, and design remains an ad hoc trial and error exercise. That makes the design of fuzzy logic controller a laborious and time-consuming task.

On the other hand, genetic algorithms (GA) are search algorithms based on the mechanics of natural selection and survival-of-the-fittest notion. The principles of GA were first introduced by Holland in his pioneering work in the theoretical development and adaptation in natural and artificial systems [11]. Recently, GA have been applied to various power system problems with promising results [12-14].

The recent approach is to integrate the use of GA and fuzzy logic systems in order to combine their different strengths [15-16]. A genetic-based fuzzy logic power system stabilizer for a single machine infinite bus system has been proposed with promising results [17]. In this paper, we extend this approach to a multimachine power system where the problem becomes more realistic and complex. The results show that the performance of FLPSSs can be significantly improved by incorporating a genetic-based learning mechanism.

2. GENETIC ALGORITHMS

GA are exploratory search and optimization procedures that were devised on the principles of natural evolution and population genetics. Unlike other optimization techniques, GA work with a population of individuals represented by bit strings and modify the population with random search and competition. The

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advantages of GA over other traditional optimization techniques can be summarized as follows:

- GA work on a coding of the parameters to be optimized, rather than the parameters themselves.
- GA search the problem space using a population of trials representing possible solutions to the problem, not a single point, i.e. GA have implicit parallelism. This property ensures GA to be less susceptible to getting trapped on local minima.
- GA use a performance index assessment to guide the search in the problem space.
- GA use probabilistic rules to make decisions.

Typically, the GA starts with little or no knowledge of the correct solution depending entirely on responses from interacting environment and their evolution operators to arrive at optimal or near optimal solutions. In general, GA include operations such as reproduction, crossover, and mutation. Reproduction is a process in which a new generation of population is formed by selecting the fittest individuals in the current population. Crossover is the most dominant operator in GA. It is responsible for producing new offsprings by selecting two strings and exchanging portions of their structures. The new offsprings may replace the weaker individuals in the population. Mutation is a local operator which is applied with a very low probability. Its function is to alter the value of a random position in a string.

3. FUZZY LOGIC CONTROL SCHEME [17]

The stabilizing signal u is added to the excitation loop as shown in Fig. 1. At time t, $u(t)$ is given by

$$u(t) = U(k) \qquad ; kT_s < t < (k+1)T_s \tag{1}$$

The value of $U(k)$ is determined at each sampling time based on fuzzy logic through the following steps:

Step 1: Consider the jth machine where the stabilizer will be installed.

Step 2: The speed deviation of the jth machine, $\Delta\omega_j(k)$, is measured at every sampling time, and the acceleration of the machine, $A_j(k)$, is calculated by

$$A_j(k) = [\, \Delta\omega_j(k) - \Delta\omega_j(k-1)\,] \,/\, T_s \tag{2}$$

Step 3: Compute the scaled acceleration, $A_{sj}(k)$, using

$$A_{sj}(k) = A_j(k) * F_{aj} \tag{3}$$

where F_{aj} is the scaling factor for the jth machine acceleration.

Step 4: The generator condition is given by the point $C_j(k)$ where

$$C_j(k) = (\, \Delta\omega_j(k) \,, A_{sj}(k)\,) \tag{4}$$

Step 5: Calculate $R_j(k)$ and $\theta_j(k)$ using

$$R_j(k) = |\, C_j(k) \,| \tag{5}$$

and,

$$\theta_j(k) = \tan^{-1} (\, A_{sj}(k) \,/\, \Delta\omega_j(k)\,) \tag{6}$$

Step 6: Compute the values of membership functions $N_{sj}(\theta_j)$ and $P_{sj}(\theta_j)$ defined as [7]

$$N_{sj}(\theta_{jj}) = \begin{cases} 1 - \Phi(x;\theta_{ij},\theta_{m1j},\theta_{mj}) \forall x \le \theta_{mj} \\ \Phi(x;\theta_{mj},\theta_{m2j},2\pi) \forall x > \theta_{mj} \end{cases} \tag{7}$$

and,

$$P_{sj}(\theta_j) = \Psi(\, \theta_j, 2\pi - \theta_{ij}, \theta_{mj}\,) \tag{8}$$

where

$$\Phi(x;a,b,c) = \begin{cases} 0.0 \ \forall \ x \le a \\ 2[\frac{x-a}{c-a}]^2 \ \forall \ x \in \left]a,b\right] \\ 1 - 2[\frac{x-c}{c-a}]^2 \ \forall x \in \left]b,c\right[\\ 1.0 \ \forall \ x \ge c \end{cases} \tag{9}$$

$$\Psi(x;b,c) = \begin{cases} \Phi(x;c-b,c-b/2,c) \ \forall x \le c \\ 1 - \Phi(x;c,c+b/2,c+b) \ \forall x > c \end{cases} \tag{10}$$

$$\theta_{mj} = (\, 2\pi + \theta_{ij}\,) / 2 \tag{11}$$

$$\theta_{m1j} = (\, \theta_{ij} + \theta_{mj}\,) / 2 \tag{12}$$

$$\theta_{m2j} = (\, 2\pi + \theta_{mj}\,) / 2 \tag{13}$$

It is worth mentioning that these continuous nonlinear membership functions are more suitable for power system stability problem [7].

Step 7: Determine the value of the gain function $G_{cj}(k)$ defined as [8]

$$G_{cj}(k) = \begin{cases} R_j(k) \,/\, D_{rj} & \forall R_j(k) \le D_{rj} \\ 1.0 & \forall R_j(k) > D_{rj} \end{cases} \tag{14}$$

Step 8: Compute the stabilizing signal $U_j(k)$ using

$$U_j(k) = G_{cj}(k) \,[\, N_{sj}(\theta) - P_{sj}(\theta)\,]\, U_{maxj} \tag{15}$$

where U_{maxj} is the maximum value of the stabilizing signal at the jth machine.

Step 9: Consider another machine where the stabilizer should be installed and go back to step 2.

Step 10: Increase k by 1 and return to step 1.

The main tuning parameters of an FLPSS are θ_{ij}, F_{aj}, and D_{rj}. For the optimal settings of these parameters, a quadratic performance index J is considered:

$$J = \sum_{i=1}^{N} \sum_{k=1}^{L} [kT_s \Delta\omega_i(k)]^2 \tag{16}$$

where N is the number of machines and L is the total number of data points.

In the above index, the speed deviation of the ith machine $\Delta\omega_i(k)$ is weighted by the respective time kT_s. The index J is selected because it reflects small settling time, small steady state error, and small overshoots. The tuning parameters are adjusted so as to minimize the index J.

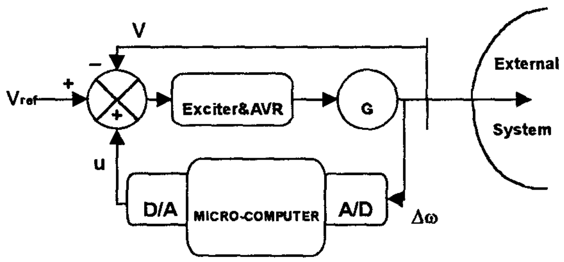


Fig. 1: Study system configuration.

4. THE PROPOSED APPROACH

The major problem in the design of conventional FLPSSs is that the stabilizers are designed one at a time and the parameters of each stabilizer are optimized iteratively [8]. This process is time consuming and the interaction between stabilizers is not taken into account. This results in degradation of the stabilizer performance. In the proposed approach, all stabilizers are designed together and all parameters are optimized simultaneously using GA as an optimization process.

Applying the GA to the problem of PSS design involves performing the following two steps.

1. The performance index value must be calculated for each of the strings in the current population. To do this, the tuning parameters must be decoded from each string in the population and the system is simulated to obtain the performance index value.
2. GA operations are applied to produce the next generation of the strings.

These two steps are repeated from generation to generation until the population converges producing an optimal or near optimal parameter set. The computational flow chart of the design process of the proposed GFLPSS is shown in Fig. 2.

The tuning parameters are coded in a binary string. The initial population is generated randomly. Population size, maximum number of generations, and crossover and mutation probabilities are chosen to be 30, 50, 0.75, and 0.005 respectively. Fig. 3 shows the convergence rate of the performance index J.

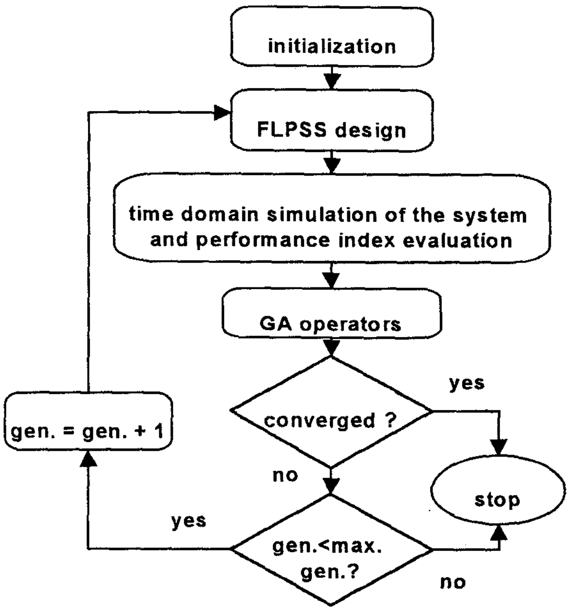


Fig. 2: Flow chart of the proposed GFLPSS design

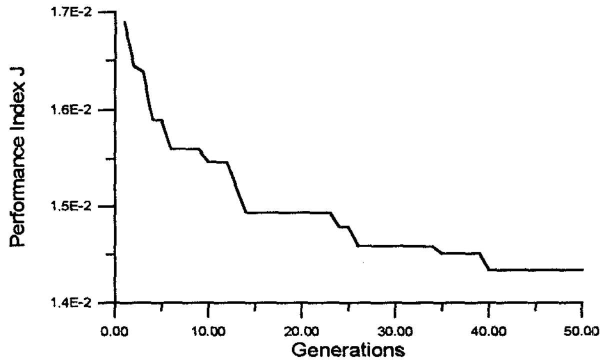


Fig. 3: Variation of the performance index J.

5. SIMULATION RESULTS

In this study, the 10-machine 39-bus New England power system shown in Fig. 4 was considered [8]. Each machine has been represented by a fourth order two-axis nonlinear model. Generator G1 is an equivalent power source representing parts of the U.S.-Canadian interconnection system. Details of the system data are given in [8]. In this study, the following disturbances are considered for the simulations:

- **(a)** Three phase fault for 0.10s at bus 29 at the end of line 26-29.
- **(b)** Three phase fault for 0.15s at bus 15 at the end of line 14-15.

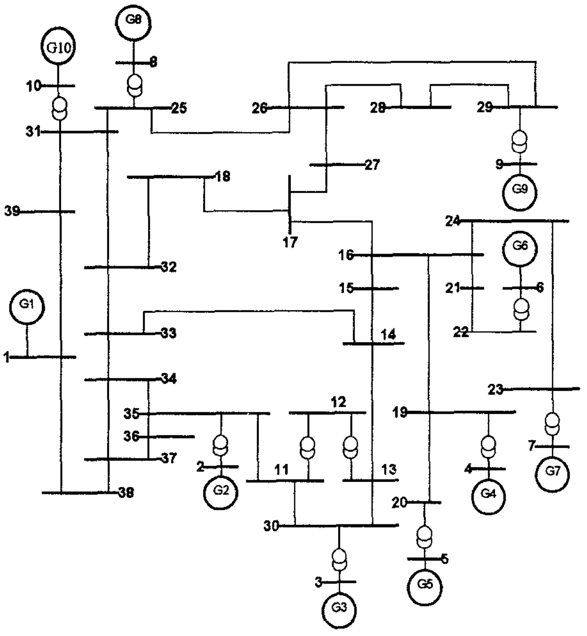


Fig. 4: Single line diagram for New England system

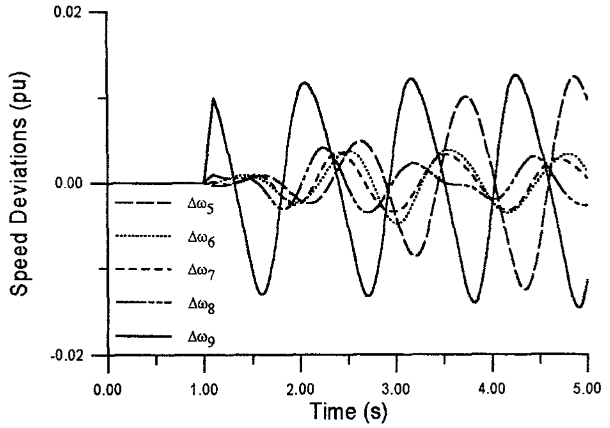


Fig. 5: System response without PSSs for disturbance (a)

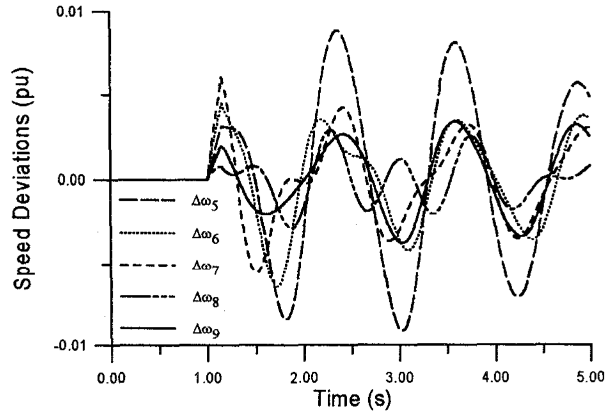
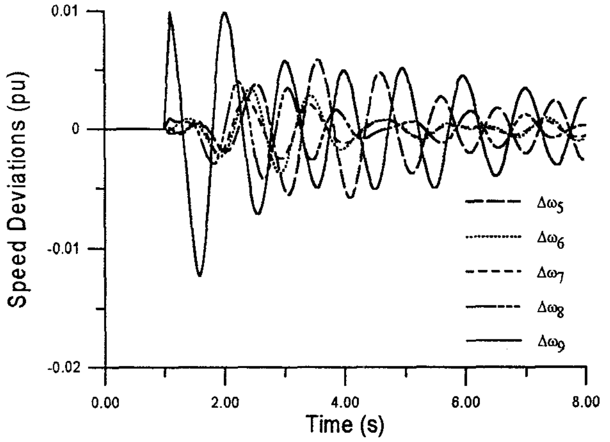


Fig. 6: System response without PSSs for disturbance (b)

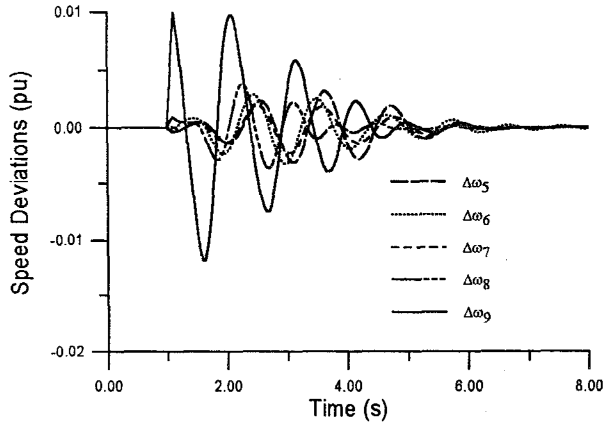
It is worth pointing out that disturbance (a) is considered to excite local mode of oscillation of the generator G9 while disturbance (b) is considered to excite interarea mode of oscillations of the system.

Without PSSs, the system responses due to disturbances (a) and (b) are shown in Figs. 5 and 6 respectively. It is observed that the system damping is very poor and the system is highly oscillatory. Therefore, it is necessary to install stabilizers in order to have good dynamic performance. To identify the optimum locations of PSSs, the participation factor method [18] and the sensitivity of PSS effect (SPE) method [19] were used. The results of both methods indicate that the generators G5, G7, and G9 are the optimum locations for installing PSSs to damp out the electromechanical modes of oscillations. Therefore, these generators are equipped with three of the proposed GFLPSSs.

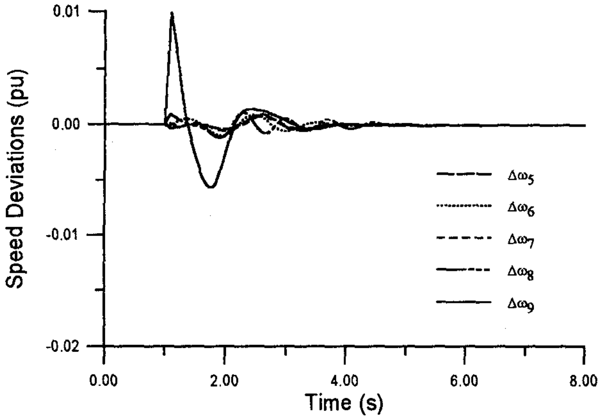
The system responses with the proposed GFLPSSs for disturbances (a) and (b) are shown in Figs. 7 and 8 respectively. In these Figs., the system performance with the proposed GFLPSSs is compared with those with CPSSs and FLPSSs [8]. The results illustrate the superiority of the proposed GFLPSSs to CPSSs and FLPSSs and its efficiency to damp out the local modes as well as the interarea modes of oscillations.



(a)



(b)



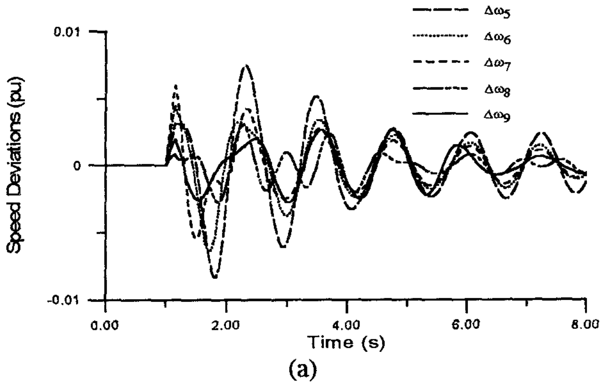
(c)

Fig. 7: System response for disturbance (a)
(a) with CPSSs
(b) with FLPSSs
(c) with proposed GFLPSSs

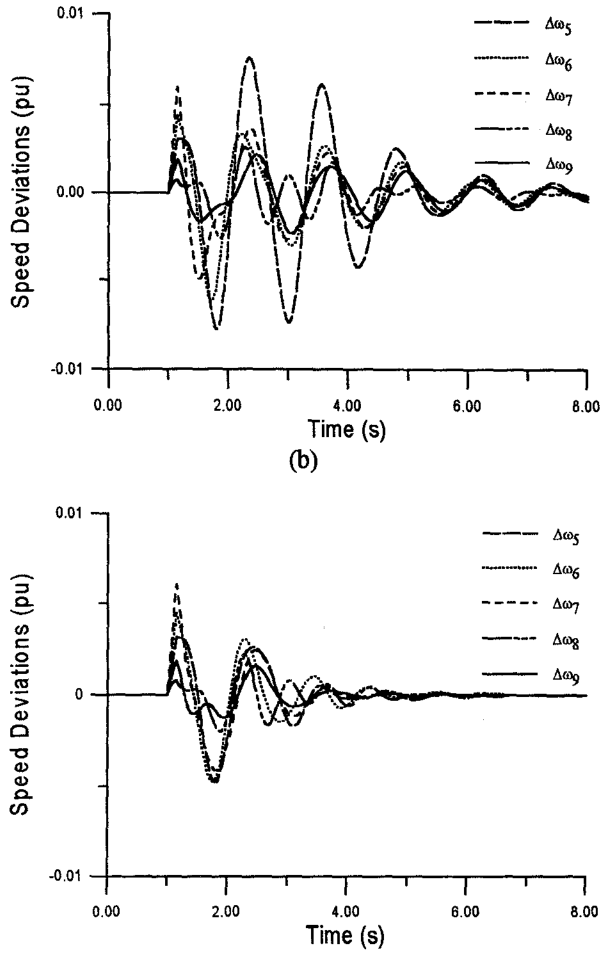
6. COORDINATION BETWEEN GFLPSS AND CPSS

In most situations, the newly installed GFLPSSs will have to work together with CPSSs which already exist in a power system. In this section, system response with the proposed GFLPSSs and CPSSs working together has been also investigated. Several combinations between the proposed GFLPSSs and CPSSs are considered as shown in Figs. 9 and 10 where C and P refer to CPSS and Proposed GFLPSS respectively. The first, second, and third letters in each combination denote the type of stabilizer installed on G5, G7, and G9 respectively.

The system responses to the disturbances (a) and (b) with different combinations are shown in Figs. 9 and 10 respectively. It can be seen that the two types of PSSs can work cooperatively. The response with the proposed GFLPSSs and CPSSs combinations is better and the oscillations are damped out much quicker than the response with only CPSSs. Generally, the system performance is improved as the number of the proposed GFLPSSs installed increases as shown in these Figures.



(a)



(c)

Fig. 8: System response for disturbance (b)
(a) with CPSSs
(b) with FLPSSs
(c) with proposed GFLPSSs

7. CONCLUSION

In this study, a genetic-based fuzzy logic power system stabilizer is introduced. The proposed GFLPSS was designed by incorporating GA to search for the optimal settings of FLPSS tuning parameters. The simulation results show that the performance of FLPSS can be improved significantly by incorporating a genetic-based learning mechanism. It is shown that the proposed GFLPSS can provide good damping characteristics during transient conditions for local as well as interarea modes of oscillations. In addition, the coordination between the proposed GFLPSS and the conventional stabilizers is demonstrated.

8. ACKNOWLEDGMENT

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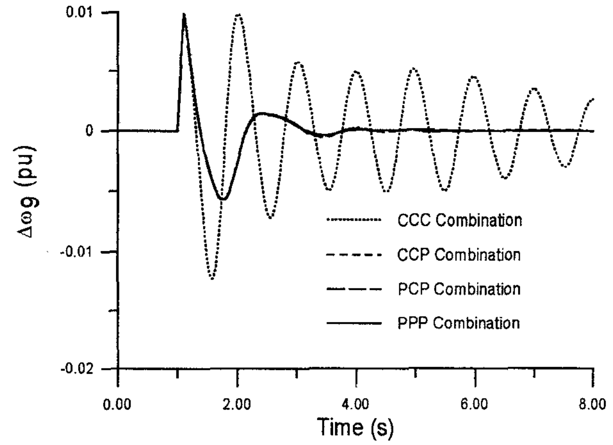

Fig. 9: System response with different combinations of PSSs for disturbance (a)

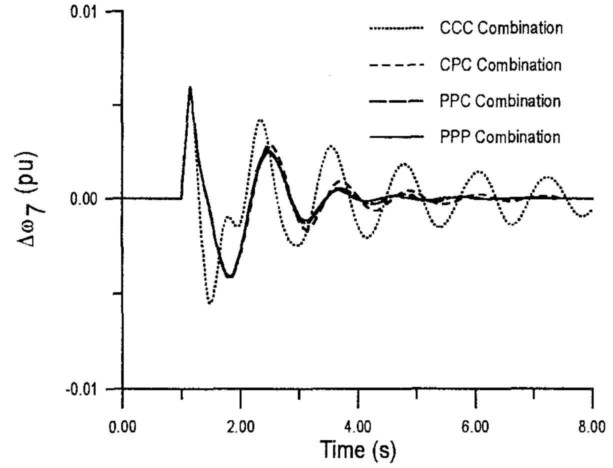

Fig. 10: System response with different combinations of PSSs for disturbance (b)

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