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Optimal Design of Multimachine Power System Stabilizers using Gbest-guided Artificial Bee Colony Algorithm

Badr M. Alshammari
College of Engineering,
University of Hail, Saudi Arabia

***Abstract*— In this paper, the concept of foraging behavior of honey bee is exploited for the optimal design of power system stabilizers. The controller design is formulated as an optimization problem in order to shift the system electromechanical modes. The dynamic performance of the proposed optimization algorithm called gbest-guided artificial bee colony algorithm has been examined at various loading conditions and under different disturbances. The proposed approach is applied to familiar multimachine power system: three machines nine bus system. The nonlinear simulations and eigenvalue analysis show the effectiveness and the robustness of the proposed stabilizers to provide efficient damping compared to famous genetic algorithm. As consequence, the system stability is greatly enhanced and both inter-area and local modes are targeted.**

Keywords*— *Power system stabilizer, Optimization problem, Artificial bee colony algorithm.

I. INTRODUCTION

The improvement of low frequency damping is an important requirement for power system security and maximum power transfer [1-2]. In some cases, these oscillations are very poorly damped and may result a serious consequence such as overload in important transmission line and fatigue at the generators. Kundur et al. [3], demonstrated that Power system stabilizers (PSSs) are very effective for damping electromechanical oscillations in power systems. The main function of PSS is to introduce damping torque to the generator rotor oscillations through the excitation system. Recently, considerable researches have been focused on the designing and using of adequate damping sources [4-8].

Several methods are developed to guarantee a high performance of PSS. In [9] the authors have explained the use of conventional lead–lag PSS in power system stability improvement. The conventional PSS (CPSS) which are designed based on linear theory has been reported in [10]. In these methods, a linear dynamic model around an operating point is usually employed. However, the parameters of real power system are time varying causing lack of robustness of the PSS controller. The application of adaptative technique for online controller required real time estimation of power system parameters. The implementation of this kind of controller may not be easy and a fixed controller is more feasible in practice. The design problem of PSS controller can be converted to an optimization problem, and several modern metaheuristic algorithms have been developed [11-13]. These algorithms can be classified into two important groups: evolutionary algorithm (EA) and swarm intelligence.

Recently, Genetic Algorithm (GA) has become the most popular evolutionary algorithm [14]. GAs simulates the phenomenon of natural evolution such as natural selection, crossover and mutation. The authors, in [15], demonstrated that the performance of PSS tuned with GAs can be significantly enhanced. Unfortunately, recent research demonstrated some limitations of GAs like high computational capacity when the problem to be optimized is complex, premature convergence [16]. The degradation in efficiency also appears, when the optimization problem presented an epistatic objective function and the number of the parameters to be optimized is large.

A global optimization algorithm, which utilizes the swarm intelligence, has received significant interest from researchers. These algorithms, attempt to simulate the behavior of natural swarms such as colony of ants, flock of birds, colony of bees, etc. In [17], the authors developed several approaches to model the intelligent behaviors of honey bees. In 2005 Karaboga introduced a swarm intelligence based algorithm called Artificial Bee Colony (ABC)[19]. It is based on foraging behavior of bee colony, which is characterized by learning, memorizing and exchanging information. In some publication [20-21], the authors demonstrated that the performance of ABC algorithm is competitive compared with other optimization techniques such as Ant colony optimization (ACO), particle swarm optimization (PSO), differential evolution (DE). Due to, its flexibility and simplicity of implementation, ABC algorithm has been used to solve many optimization problems.

The solution search equation of ABC is poor at exploitation and good in exploration. In order to achieve good performance in optimization problems, the two aspects should be well balanced. In practice the two abilities contradicts to each other. In [18], the authors proposed a solution of the mentioned drawback based on the modification of the solution search equation .This approach aims to improve the exploitation by applying the global best (gbest) solution in order to guide the search of new candidate solutions. This type of ABC is called Gbest-guided ABC (GABC) algorithm.

The rest of this paper is structured as follows. In Sect. 2 we introduce the power system model. Section 3 describes the design of the damping controller. The original and the Gbest-guided artificial bee colony algorithm (GABC) are presented in Section 4. Section 5 presents and discusses the results. Finally, the conclusion is drawn in Section 6.

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II. SYSTEM MODELING

A. Synchronous machine model

In this study, the synchronous machine is modeled as one axis model. The third order nonlinear differential equations for any i-th machine are expressed as follows [1].

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

$$\dot{\omega}_i = \frac{1}{M_i}\left(P_{mi} - P_{ei} - D_i\left(\omega_i - 1\right)\right) \tag{2}$$

$$\dot{E}'_{qi} = \frac{1}{T'_{d0i}}\left(E_{fdi} - \left(x_{di} - x'_{di}\right) i_{di} - E'_{qi}\right) \tag{3}$$

Where δ_i and ω_i are rotor angle and angular speed of the machine. ω_b is the base frequency in rad/sec. P_{mi} and P_{ei} are the mechanical input and the electrical output powers for the machine i, respectively. D_i and M_i are the damping coefficient and inertia constant, respectively. E_{fdi} and E'_{qi} are the field and the internal voltages, respectively. i_d is the d-axis armature current .

x_d and x'_d are the d-axis transient reactance and the d-axis reactance of the generator, respectively. T'_{d0} is the open circuit field time constant.

The electrical torque T_e can be expressed by

$$T_e = E'_{qi}\, i_{qi} - \left(x_{qi} - x'_{di}\right) i_{di}\, i_{qi} \tag{4}$$

B. Excitation system with PSS structure

The PSS acts through the exciter and provides control effect to the power system under study [3]. The IEEE type-ST1 excitation system with PSS shown in Fig. 1 is considered in this paper. Where, K_{Ai} and T_{Ai} are the regulator gain and the regulator time constant of the excitation system, respectively. V_{refi} and V_{ti} are reference and generator terminal voltages of the i-th machine, respectively. The field voltage can be modeled by the following equation :

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}\left(-E_{fdi} + K_{Ai}\left(V_{refi} - V_{ti} + U_i\right)\right) \tag{5}$$

As shown the Fig.1, the PSS representation consists of a gain K_i, a washout block with time constant T_{wi} and two lead–lag blocks. Its input signal is the normalized speed deviation, $\Delta\omega_i$. While, the output signal is the supplementary stabilizing signal, U_i. As given in the bloc diagram of Fig. 1, the transfer function of the PSS is given below.

$$U_i = K_i \frac{s\,T_{wi}}{1+s\,T_{wi}}\left[\frac{\left(1+s\,T_{1i}\right)\left(1+s\,T_{3i}\right)}{\left(1+s\,T_{2i}\right)\left(1+s\,T_{4i}\right)}\right]\Delta\omega_i \tag{6}$$

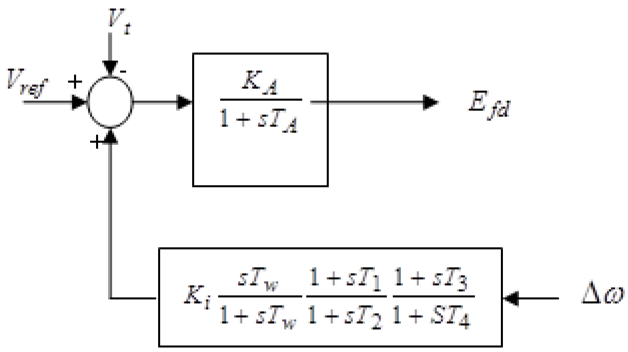

Fig. 1. IEEE Type-ST1 excitation system with PSS

In the previous equation, the washout bloc with time constant T_W is used as high-pass filter to leave the signals in range 0.2-2 Hz associated with rotor oscillation to pass without change. In general, it is in the range of 1-20 s. In this study, $T_w = 5s$ .The two first order lead-lag transfer function serve to compensate the phase lag between the PSS output and the control action which is the electrical torque.

III. DAMPING CONTROLLER DESIGN

After linearizing the power system model around the operating point, the closed-loop eigenvalues of the system are computed and the desired objective functions can be formulated using only the unstable or lightly damped electromechanical modes that need to be shifted.

In this paper, two eigenvalue objective functions are considered, in order to solve the problem of parameters tuning of the PSS controllers. The first one consists in shifting the closed-loop eigenvalues in to the left-side of the line defined by $\sigma = \sigma_0$. This function is expressed by J_1 in equation (7). In equation (8), J_2 defines the second objective function. It will place the closed-loop eigenvalues in a wedge-shape sector corresponding to $\xi_{i,j} \geq \xi_0$. As consequence, the maximum overshoot is limited.

$$J1 = \sum_{j=1}^{np} \sum_{\sigma_{i,j} \geq \sigma_0} \left(\sigma_0 - \sigma_{i,j}\right)^2 \tag{7}$$

$$J2 = \sum_{j=1}^{np} \sum_{\xi_{i,j} \leq \xi_0} \left(\xi_0 - \xi_{i,j}\right)^2 \tag{8}$$

Where np is number of operating points and $\sigma_{i,j}$ and $\xi_{i,j}$ are respectively, real part and damping ratio of the i-th eigenvalue corresponding to the j-th operating point.

Therefore, the design problem is aimed to minimize an eigenvalue based multi-objective function J obtained by combination J_1 and J_2 . In order to offset the weight of the first and the second objective function a weight factor " a" is used. The multi-objective function J is given by the following expression [22].

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$$J = \sum_{j=1}^{np} \sum_{\sigma_{i,j} \geq \sigma_0} \left(\sigma_0 - \sigma_{i,j} \right)^2 + a \sum_{j=1}^{np} \sum_{\xi_{i,j} \leq \xi_0} \left(\xi_0 - \xi_{i,j} \right)^2 \quad (9)$$

The closed-loop eigenvalues will be placed in the D-shape sector. In the design process the adjustable parameter bounds given by equations (10)-(14) must be respected.

The adjustable parameters bounds are formulated as follows:

$$K^{\min} \leq K \leq K^{\max} \quad (10)$$

$$T_1^{\min} \leq T_1 \leq T_1^{\max} \quad (11)$$

$$T_2^{\min} \leq T_2 \leq T_2^{\max} \quad (12)$$

$$T_3^{\min} \leq T_3 \leq T_3^{\max} \quad (13)$$

$$T_4^{\min} \leq T_4 \leq T_4^{\max} \quad (14)$$

IV. Gbest-guided ABC (GABC) algorithm

A. *Artificial Bee Colony algorithm description*

The artificial Bees colony (ABC) Algorithm is an optimization algorithm which simulates the natural foraging behavior of honey bees to find the optimal solution[19]. A colony of honey bees consists of three groups of bees, employed bees, onlooker's bees and scouts. The first half of colony consists of employed bees which are responsible for exploring food sources. These bees go to their food sources and come back to hive and dance on this area. The onlooker bees wait in the hive and choose food source to exploit. This decision is depending on employed bees dances. When food sources are exhausted, the employed bees become scouts and start to search in the environment for finding new food sources. The main steps of the ABC algorithm are summarized as follows:

1. At first, bees explore the search space randomly in order to find a food source.
2. When the food source is found, the employed bees start to load the nectar. Then they return to the hive to unload the nectar. These bees share information about their source with onlooker bees through a dance in the dance area. The probability of food choice depends on nectar amount information distributed by the employed bees.
3. The employed bee whose food source has been exhausted, become scouts and starts to search for a new source randomly.

The proposed algorithm involves five steps [23]:

Step1: In the ABC algorithm a possible solution of the optimization problem is represented by a position of food source. The population size of food source is SN and the number of the parameters to be optimized is D. The initialization phase starts with producing food source randomly within the range of the boundaries via the following expression

$$x_{ij} = x_j^{\min} + rand\,(0,1)\,(x_j^{\max} - x_j^{\min}) \quad (15)$$

Where $x_j^{\max}$ and $x_j^{\min}$ are the upper and the lower of a food source.

Step2: As mentioned earlier the number of food source sites is equal to the number of employed bees. An employed bee searches a neighborhood of its current solution based on visual information. The new food source is described by

$$v_{ij} = x_{ij} + \varphi_{ij}\,(x_{ij} - x_{kj}) \quad (16)$$

It must be noted that ϕ_{ij} is a random number in the range $[-1,1]$ and k has to be different from i. In this work, if the values of the parameters produced by the previous equation exceed their boundaries, the parameters are set to their boundaries values as follows:

$$\begin{cases} If \quad x_i \succ x_i^{\max} & x_i = x_i^{\max} \\ If \quad x_i \prec x_i^{\min} & x_i = x_i^{\min} \end{cases} \quad (17)$$

For a minimization problem, the neighborhood solution v_i can be evaluated through (18)

$$fitness = \begin{cases} 1/(1+f_i) & if \quad f_i \geq 0 \\ 1+abs(f_i) & if \quad f_i \prec 0 \end{cases} \quad (18)$$

Step3: An onlooker bee selects a food source based on the information distributed by the employed bees. The probability of selection of the food source xi is defined by

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \quad (19)$$

Where is the fitness value of food source.

Once probabilistic selection is completed, the onlooker bees produce a new food source using eq.(16). After generation a new food source, it will be evaluated and greedy selection will be performed.

Step 4: The food source whose number of trials exceeds the predetermined limit, are considered to be exhausted and is abandoned. The employed bees associated with exhausted source become a scout. It is assumed that only one employed bee at each cycle can become a scout. The scout generates randomly a new food source for replacing the abandoned source.

Step 5: The process is stopped, when the termination condition is met and the best food source is memorized. Otherwise repeat the algorithm since the second step.

B. *Gbest-guided ABC*

It is important to point out, that exploitation and exploration are necessary for evolutionary algorithms. The exploitation refers to the ability to use the knowledge of the previous good solutions to generate a better candidate solution. While, the exploration refers to the ability to seek in the various unknown regions of the solutions space to discover the global optimum. in order to achieve good optimization performance the two ability should be well balanced. The search equation of ABC described by Eq. (16) is poor in exploitation, so the new candidate solution is not promising to be better than the previous one.

To improve exploitation, Zhu and Kwong [18] proposed to incorporate the global best solution (gbest) into the solution search equation which described as follows

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) + \psi_{ij}\left(y_j - x_{ij}\right) \quad (20)$$

Where the new added term is called global best (gbest) term, y_j is the jth element of the global best solution, and ψ_{ij} is a uniformly distributed random number in [0,C], where C is a positive constant.

V. RESULTS AND DISCUSSIONS

A. *Test system*

In this study, the 3-machine 9-bus (WSSC) shown in Fig. 2 is considered.. The system data in detail is given in [2].It is assumed that all generators except G1 are equipped with PSS [4].

B. *PSS tuning*

To compute the optimum value of the proposed GABCPSS, three operating conditions are considered. The generators operating conditions and the loads are listed in table I. The system eigenvalues and damping ratio of mechanical mode for all loading conditions, both with GAPSS, GABCPSS and without PSS are given in table II. It is clear, when the PSS is not mounted, the electromechanical modes are poorly damped and both of them are unstable.

There are 10 parameters to be optimized which are K_i, T_{1i}, T_{2i}, T_{3i} and T_{4i}. The washout time constant and weighting factor "a" are set to be 5 s and 10 respectively. In designing the objective function to be optimized, the value of σ_0 and ξ_0 are chosen to be -1.5 and 0.20.

It is quite clear that the proposed GABCPSS is able to shift all electromechanical mode in the D-shape sector specified by $\xi \geq 0.2$ and $\sigma \leq -1.5$. Hence, compared to GAPSS, the proposed GABCPSS greatly enhances the system damping and the dynamic stability is significantly improved.

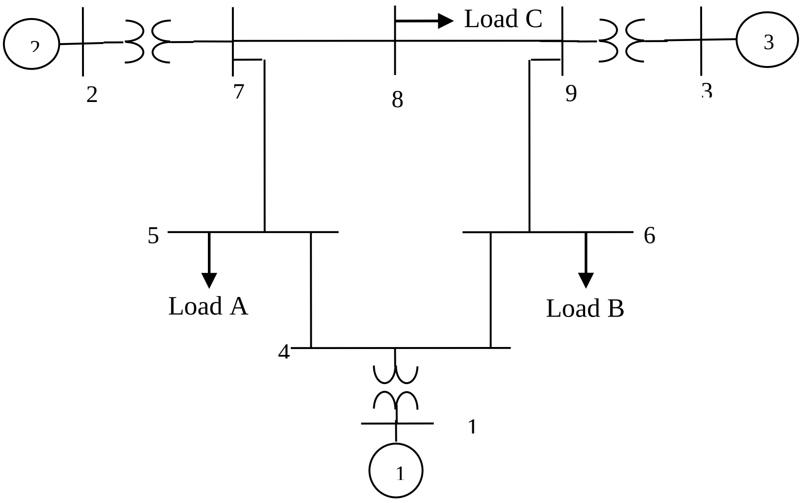

Fig. 2. Single line diagram for the 3-machine 9-bus

Table I. Loading conditions for the system (in p.u).

Generator	Base Case		Case 1		Case 2		Case 3	
	P [pu]	*Q* [pu]	*P* [pu]	*Q* [pu]	*P* [pu]	*Q* [pu]	*P* [pu]	*Q* [pu]
G_1	0.72	0.27	2.21	1.09	0.36	0.16	0.33	1.12
G_2	1.63	0.07	1.92	0.56	0.80	-0.11	2.00	0.57
G_3	0.85	-0.11	1.28	0.36	0.45	-0.20	1.50	0.38
Load								
A	1.25	0.50	2.00	0.80	0.65	0.55	1.50	0.90
B	0.90	0.30	1.80	0.60	0.45	0.35	1.20	0.80
C	1.00	0.35	1.50	0.60	0.50	0.25	1.00	0.50

TABLE II. ELECTROMECHANICAL MODE AND DAMPING RATIOS OF TEST SYSTEM UNDER DIFFERENT LOADING CONDITIONS

	Without PSS	GAPSS	GABCPSS
Base Case	-0.1124±*j* 7.7400, 0.0145	-1.8096± 4.5504, 0.3695	-2.6760± *j* 4.6586, 0.4981
	-1.3346±*j* 9.1096, 0.1450	-2.4897± 7.5480, 0.3132	-2.6097± *j* 9.6042, 0.2622
Case 1	-0.0374±*j* 7.8347, 0.0048	-1.9889± *j* 5.6843, 0.3303	-2.2596± *j* 5.1552, 0.4014
	-0.7023±*j* 10.5832, 0.0662	-2.5204± *j* 7.3736 , 0.3234	-2.6756± *j* 11.1852, 0.2326
Case 2	-0.2142±*j* 6.3226, 0.0339	-1.5189± *j* 4.1628, 0.3428	-2.2717± *j* 4.3849, 0.4600
	-0.8227±*j* 6.9390, 0.1177	-1.4789± *j* 6.1042, 0.2355	-1.9109± *j* 7.6704, 0.2417
Case 3	**0.0181±*j* 8.0903**, - 0.0022	-2.2779± *j* 5.6069, 0.3764	-2.5524± *j* 5.1564, 0.4436
	-0.4515±*j* 11.3794, 0.0396	-2.2162± *j* 7.7961, 0.2734	-2.6455± *j* 12.0431, 0.2146

The result of the PSS controller parameters set values based on multiobjective function using both the proposed GABC and GA are given in table III. Fig. 3 shows the convergence rate of the objective function with two optimization techniques which are GABC and GA. When the final value of the multiobjective function is J = 0 for two algorithms, the electromechanical modes are restricted in the specified D-shape sector. Also, the parameters of both methods are given in table IV. In order to obtain global optimal solution, the optimization algorithms(GABC and GA) are run several times and then the optimum PSS parameters are selected.

TABLE III. OPTIMAL PARAMETERS OF THE PROPOSED ABCPSS

Methods	Gen	K	T_1	T_2	T_3	T_4
GAPSS	G_2	8.6355	0.7053	0.3223	0.1809	0.3523
	G_3	1.6280	0.3325	0.1976	1.3654	0.1687
GABCPSS	G_2	10.0000	0.2226	0.3334	0.6000	0.1381
	G_3	8.6432	0.0500	0.2575	0.3780	0.2780

A. Nonlinear time domain simulation

To demonstrate the robustness of the proposed PSSs tuned over wide range of loading conditions and using the proposed multiobjective function, the following scenarios are considered:

C.1 .Scenario 1

In this scenario, a six cycle three phase fault at bus 7 at the end of line 5-7 is considered. This severe disturbance is cleared without line tripping. The rotor speed deviation of generator for three operating conditions are shown in Figs.4–7. From these figures, it can be seen that the response with GABCPSS controllers show good damping characteristics to low frequency oscillations and the system is more quickly stabilized than GAPSS.

Furthermore, the proposed controllers have better performance in term of settling time and overshoots compared to other controllers. With changing operating conditions from the base case to case three, while the performance of GAPSS become poorer, the GABCPSS have robust and stable performances. This confirms the superiority of GABC design approach over GA design approach.

TABLE IV. GABC AND GA PARAMETERS

GABC algorithms	*Genetic algorithms*
Number of colony size = 100	Population size = 100
Food number = 50	Number of chromosome = 9
Maximum cycle number = 100	Mutation rate = 0.05
Number of trials "Limit" = 80	Cross over rate = 0.5
	Number of iterations = 100

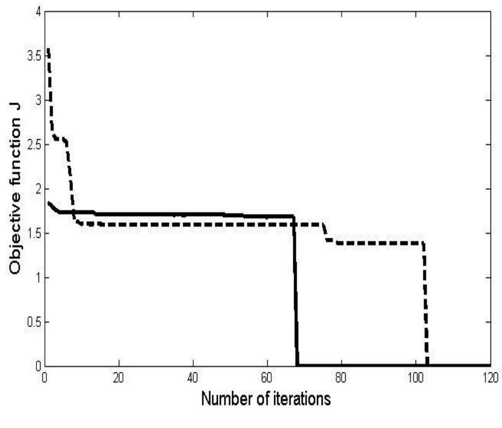

Fig.3. Variations of objective function; solid (GABC), dashed (GA)

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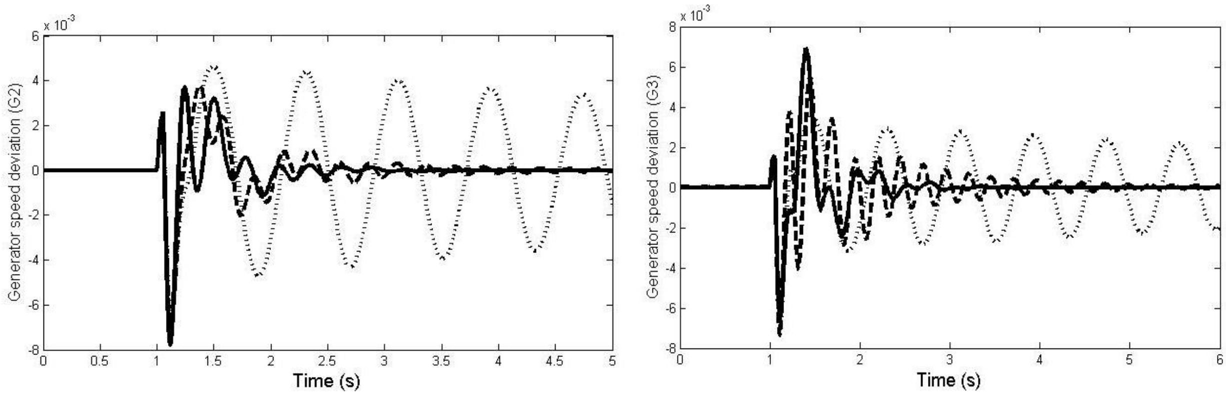

Fig 4. Speed response for 6-cycle fault with base case in scenario 1; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS).

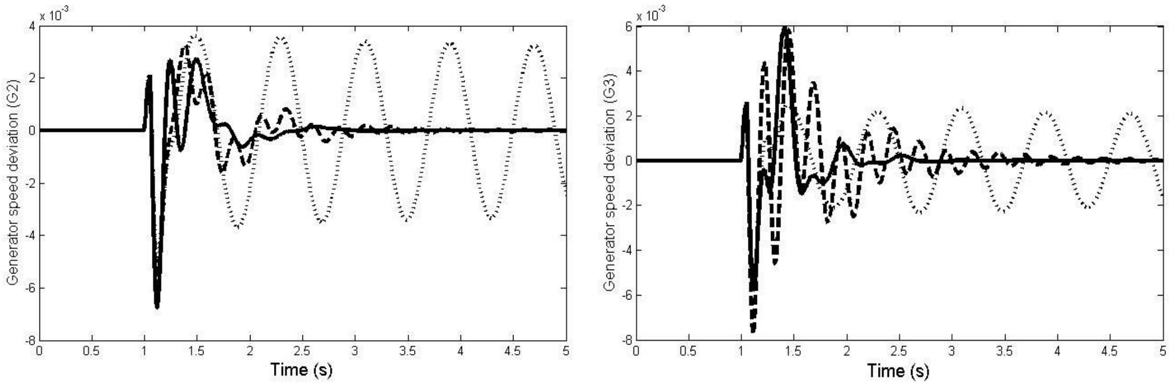

Fig 5. Speed response for 6-cycle fault with case1 in scenario 1; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS)

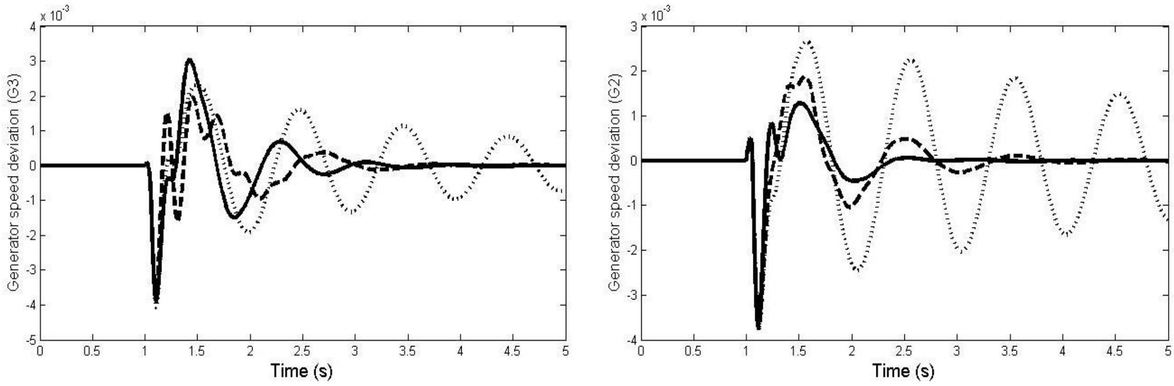

Fig 6. Speed response for 6-cycle fault with case 2 in scenario 1; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS)

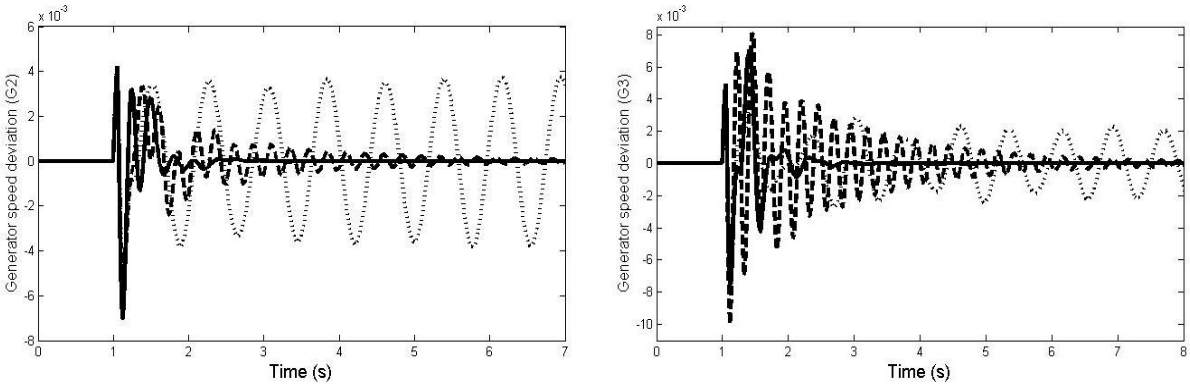

Fig 7. Speed response for 6-cycle fault with case 3 in scenario 1; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS).

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C.2 .Scenario ***2***

A more severe disturbance, of a six cycle three phase fault at bus 7 at the end of line 5-7 is considered. The fault is cleared by permanent tripping of the fault line. Fig.8-11 show the speed deviation of the second and the third machines under for operating conditions. The results show that the test power system is adequately damped when the GABCPSS is mounted. These responses are consistent with the results of eigenvalue analysis. In addition, it can be seen that GABC base PSSs enhances significantly the first swing stability. This illustrates the potential of the proposed approach to select an optimal set of PSSs parameters.

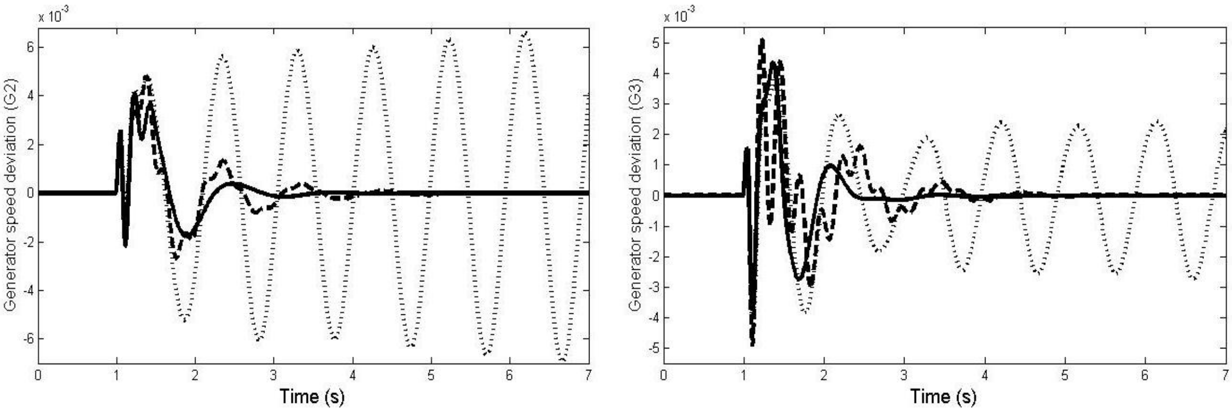

Fig. 8. Speed response for 6-cycle fault with base case in scenario 2; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS).

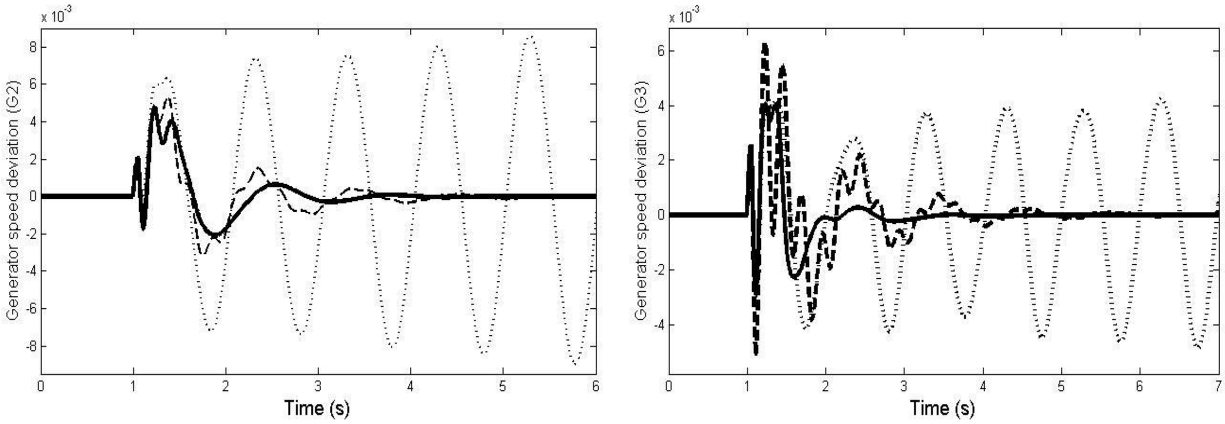

Fig. 9. Speed response for 6-cycle fault with case1 in scenario 2; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS).

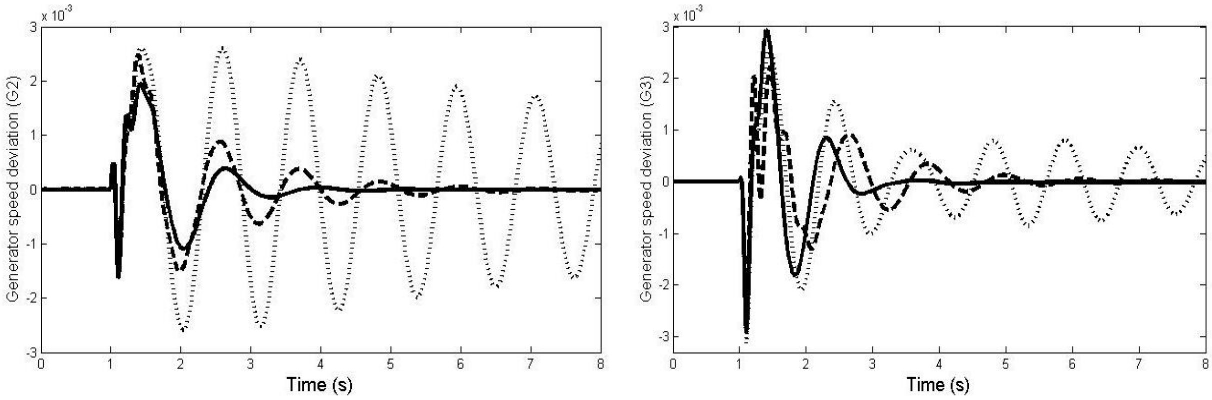

Fig. 10. Speed response for 6-cycle fault with case 2 in scenario 2; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS)

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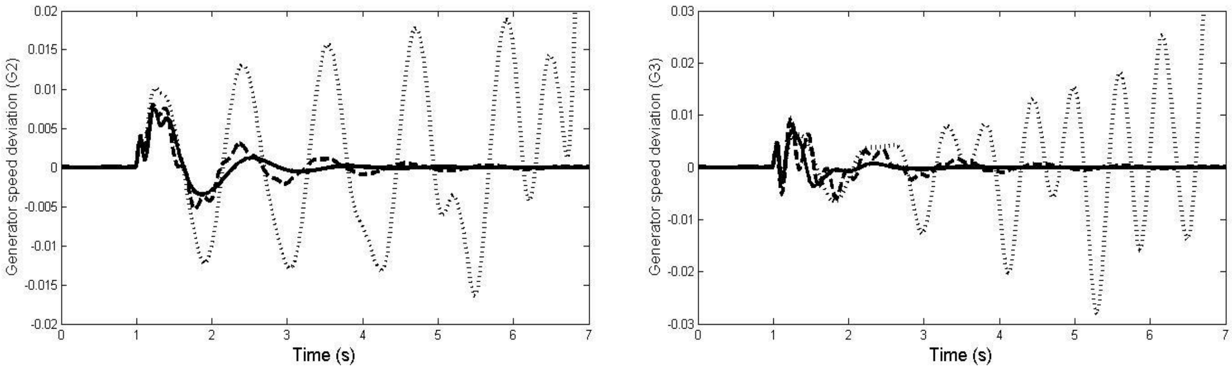

Fig. 11. Speed response for 6-cycle fault with case 3 in scenario 2; solid (GABCPSS), dashed (GAPSS) and dotted (without PSS)

C.3. Performance investigation

To analyze performance robustness of the proposed stabilizers a performance index: the Integral of the Time multiplied Absolute value of the Error (ITAE) is considered as follows:

$$ITAE = 100 \times \int_{0}^{t_{sim}} t\left(|\Delta\omega_2| + |\Delta\omega_3|\right)dt \qquad (20)$$

It is to be mentioned that the lower value of this index reflect the better system response characteristics. The ITAE is calculated for two scenarios and at all operating conditions and the results are shown in table V. It can be seen that the values of these system performance index with GABCPSS are much smaller compared to GA tuned controller. This demonstrate that the application of the proposed GABCPSS reduce greatly the settling time, overshoot, undershoot and speed deviations. Moreover, these values of the ITAE are smaller than those obtained in [24].

TABLE V. VALUES OF PERFORMANCE INDEX (ITAE) FOR DIFFERENT CONDITIONS

	Scenario 1				Scenario 2			
	Base Case	Case 1	Case 2	Case 3	Base Case	Case 1	Case 2	Case 3
GABC-PSS	0.6286	0.4888	0.4482	0.5784	0.7748	0.8263	0.6459	1.3606
GA-PSS	1.2357	0.9603	0.5492	3.1383	1.1614	1.5437	1.0990	3.2127

VI. CONCLUSION

In this paper, the Gbest-guided artificial bee colony algorithm (GABC) has been successfully applied for power system stabilizer design. The problem of robust PSS is converted to an optimization problem according to eigenvalue based objective function which is solved by GABC algorithm. The effectivness of the proposed design strategy is tested on a multimachine power system subject to severe disturbances for wide range of operating conditions. The nonlinear simulation shows that the proposed GABCPSS controller enhances greatly the dynamic stability over wide range of loading conditions. The eigenvalue analysis reveals that the electromechanical modes are shifted to the left in s-plane. The system performance index demonstrates the superiority of the proposed stabilizers compared to GA based tuned stabilizers.

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BIOGRAPHY

Badr M. Alshammari obtained his B.Sc., M.Sc. and Ph.D. degrees from King Saud University, Riyadh, Saudi Arabia in 1998, 2004 and 2012, respectively. He is currently an Assistant Professor and Vice Dean for Quality & Development, College of Engineering at University of Hail, Hail, Saudi Arabia. He is a chairman of the Research Committee in the college of Engineering and member of the Research Committee at the Hail University. His main research area of interest is Power System Reliability and Optimized Performance of Electricity Systems.