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Optimal Location and Optimized Parameters for Robust PSS Using Honey Bee Mating Optimization

[1]A. Ghasemi, [2]O. Abedinia, [3]F. Javidzadeh and [3]D. Garmarodi

[1]Islamic Azad University, Young Researcher Club, Ardabil Branch, Ardabil, Iran
[2]Department of Technical Engineering, University of Mohaghegh Ardabili, Ardabil, Iran
[3]Islamic Azad University, Science and Research Branch, Tehran, Iran

Abstract: A Honey Bee Mating Optimization (HBMO) technique is used to tune the Power System Stabilizer (PSS) parameters and find optimal location of PSSs in this paper. The PSS parameters and placement are computed to assure maximum damping performance under different operating conditions. One of the main advantages of the proposed approach is its robustness to the initial parameter settings. The effectiveness of the proposed method is demonstrated on two case studies as; two-area four-machine (TAFM) system of Kundur in comparison with the Strength Pareto Evolutionary Algorithm (SPEA), Genetic Algorithm (GA) and Quantitative Feedback Theory (QFT) and 10 machine 39 bus New England power system in comparison with Tabu Search (TS) through FD, ITAE and ζ performance indices under different operating condition. 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: Optimal Placement · HBMO · PSS · Multi-machine Power System

INTRODUCTION

Power systems are inherently nonlinear and undergo a wide range of transient conditions, that results in under damped low frequency speed as well as power oscillations that are difficult to control. The generator excitation system maintains generator voltage and controls the reactive power flow using an automatic voltage regulator (AVR).The role of an AVR is to hold the terminal voltage magnitude of a synchronous generator at a specified level. AVR helps to develop the steady-state stability of power systems; however transient stability became a concern for the power system operators [1]. The damping of power system oscillations plays an important role in enhancing overall system stability. In recent decades, power-system stabilizers (PSSs) with conventional industry structure have been extensively used in modern power systems as an efficient means of damping power oscillations [2].

Conventional power system stabilizers (CPSSs) are designed based on linear models representing the system's generators operating at a certain operating point. The performance of these designed CPSSs is acceptable as long as the system is operating close to the operating point for which the system model is obtained. However, CPSSs are not able to provide satisfactory performance results over wider ranges of operating conditions.To overcome these difficulties of PSS design and location of that, intelligent optimization based techniques have been introduced [3].

H8 optimization techniques [4-5] have been applied to robust PSS design problem. However, the additive and/or multiplicative uncertainty representation cannot treat situations where a nominal stable system becomes unstable after being perturbed. On the other hand, the order of the H8 based stabilizer is as high as that of the plant. This gives rise to complex structure of such stabilizers and reduces their applicability.

Genetic algorithm (GA) is a powerful optimization technique, independent on the complexity of problems where no prior knowledge is available. Many PSS tuning methods use GA [6-9]. These works investigated the use of genetic algorithms for simultaneously stabilization of multi-machine power system over a wide range of

Corresponding Author: A. Ghasemi, Islamic Azad University, Young Researcher Club, Ardabil Branch, Ardabil, Iran.

scenarios via power system stabilizers with fixed parameters. In [10] formulates the robust PSS design as a multi-objective optimization problem and employs GA to solve it. Improving damping factor and damping ratio of the lightly damped or un-damped electromechanical modes are two objectives. It has been shown that taking just one of the objectives into account may yield to an unsatisfactory result for another one. Also GA is very sufficient in finding global or near global optimal solution of the problem, it requires a very long run time that may be several minutes or even several hours depending on the size of the system under study [6, 11].

Artificial Neural Network (ANN) is an intelligent method which is used for PSS tuning [12]. This technique has its own advantages and disadvantages. The performance of power system is improved by ANN based controller but, the main problem of these controllers are the long training time and selecting the number of layers and number of neurons in each layers [13]. Also, the proposed techniques are iterative and require heavy computation burden due to system reduction procedure. To overcome the backwashes of above methods, HBMO is proposed to optimization in this paper.

To overcome these drawbacks Honey-bee mating optimization (HBMO) is proposed. HBMO may also be considered as a typical swarm-based approach for optimization, in which the search algorithm is inspired by the process of mating in real honey-bees. The behavior of honey-bees is the interaction of their: 1- genetic potentiality, 2- ecological and physiological environments and 3- the social conditions of the colony, as well as various prior and ongoing interactions between these three parameters. In the literature, the honey-bee mating may also be considered as a typical swarm-based approach for searching for the optimal solution in many application domains such as clustering [14], market segmentation [15] and benchmark mathematical problems [16].

The two-area four-machine TAFM system, under various system configurations and loading conditions is employed to illustrate the effectiveness of the proposed method for placement in comparison with the Strength Pareto Evolutionary Algorithm (SPEA), Genetic Algorithm (GA) [11]. And the effectiveness of the proposed method for PSS parameters tuning is compared via Quantitative Feedback Theory (QFT) [17]. Also 10 machine 39 buses New England power system is applied to illustrate the effectiveness of the optimal location and parameters in comparison with Tabu Search (TS) [18] through FD, ITAE and ζ performance indices under different operating condition. The Results evaluation show that the proposed method is effective and alternative to conventional fixed gain stabilizer design as it retains the simplicity of the conventional PSS and still guarantees a robust acceptable performance over a wide range of operating and system condition.

Power System Description: The complex nonlinear model related to an n-machine interconnected power system for case 2, 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. The synchronous machine is the most important part of power systems. This part of power system includes electromechanical system which is made of two parts as: electrical and mechanical parts. The model of power system in this paper is simulated by deferential equations that are presented below for this paper [19]. Description of these parameters is presented in APPENDIX A.

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

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

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

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}(K_{Ai}(v_{refi} - v_i + u_i) - E_{fdi}) \tag{4}$$

$$T_{ei} = E'_{qi}i_{qi} - (x_{qi} - x'_{di})i_{di}i_{qi} \tag{5}$$

HBMO Technique: The honey bee is a social insect that can survive only as a member of a community, or colony. The colony inhabits an enclosed cavity. A colony of honey bees consist of a queen, several hundred drones, 30,000 to 80,000 workers and broods during the active season. A colony of bees is a large family of bees living in one bee-hive. The queen is the most important member of the hive because she is the one that keeps the hive going by producing new queen and worker bees [20]. Drones' role is to mate with the queen. Tasks of worker bees are several such as: rearing brood, tending the queen and drones, cleaning, regulating temperature, gather nectar, pollen, water, etc. Broods arise either from fertilized (represents queen or worker) or unfertilized (represents drones) eggs. The HBMO Algorithm is the combination of several different methods corresponded to a different phase of the mating process of the queen. In the marriage process, the queen(s) mate during their mating flights far from the nest. A mating flight starts with a dance performed by the queen who then starts a mating flight during which the drones follow the queen and mate with her in the air. In each mating, sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony. The queen's size of spermatheca number equals to the maximum number of mating of the queen in a single mating flight is determined. When the queen mates successfully, the genotype of the drone is stored. At the start of the flight, the queen is initialized with some energy content and returns to her nest when her energy is within some threshold from zero or when her spermatheca is full. In developing the algorithm, the functionality of workers is restricted to brood care and therefore, each worker may be represented as a heuristic which acts to improve and/or take care of a set of broods. A drone mates with a queen probabilistically using an annealing function as [21]:

$$P_{rob}(Q,D) = e\frac{\Delta(f)}{s(t)} \tag{6}$$

where P_{rob} (*Q, D*) is the probability of adding the sperm of drone *D* to the spermatheca of queen *Q* (that is, the probability of a successful mating); *Δ*(*f*) is the absolute difference between the fitness of *D* (i.e., *f* (*D*)) and the fitness of *Q* (i.e., *f* (*Q*)); and *S*(*t*) is the speed of the queen at time t. It is apparent that this function acts as an annealing function, where the probability of mating is high when both the queen is still in the start of her mating–flight and therefore her speed is high, or when the fitness of the drone is as good as the queen's. After each transition in space, the queen's speed, *S*(*t*) and energy, *E*(*t*), decay using the following equations:

$$S(t+1) = \propto \times S(t)\ (2) \tag{7}$$

$$E(t+1) = E(t) = \mathrm{E}(t) - \gamma \tag{8}$$

where $\propto$ is a factor $\in[0,1]$ and γ is the amount of energy reduction after each transition. Thus, HBMO algorithm may be constructed with the following five main stages [22]:

- The algorithm starts with the mating–flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones). A drone is then selected from the list at random for the creation of broods.
- Creation of new broods by crossoverring the drones' genotypes with the queen's.
- Use of workers (heuristics) to conduct local search on broods (trial solutions).
- Adaptation of workers' fitness based on the amount of improvement achieved on broods.
- Replacement of weaker queens by fitter broods.

Also, Algorithm and computational flowchart of HBMO method for optimize the PID parameters is presented in Fig. 1.

Problem Statement

PSS Design: The problem of setting the parameters and locations of PSSs that assure maximum damping performance is solved using a GAs optimization procedure. For every operating condition, a linearized model is obtained. A widely used conventional lead-lag PSS is considered in this study [3]. It can be shown at Fig. 2.

The CPSS consists of two phase-lead compensation blocks, a signal washout block, a filter, a measurement delay, a limiter and a gain block. The PSS parameters construct the decision vector. For optimize, these parameters are experimentally limited. These limitations reduce the computational times significantly. Table 1-2 show the low and up boundaries of the parameters in case 1 and case 2 respectively.

Case Study 1

Two-Area Four-Machine System: Kundur's Two-Area Four-Machine (TAFM) system consisting of two fully symmetrical areas linked together by two 220 km, 230 kV transmission lines is the studied system in this paper [17]. This power system typically is used to study the low frequency electromechanical oscillations of a large interconnected system. Fig. 3 shows the system and its data which is available for anyone in Matlab software's demo.

Applying HBMO Algorithm to TAFM System: To increase the system damping to the electromechanical modes and find appropriate location of PSSs the objective function f defined below is proposed:

$$f = \sum_{n=1}^{N_{load}} \left\{ \int_0^{t_{sim}} \{ |\, \omega_{G1} + \omega_{G2} + \omega_{G3} + \omega_{G4} \,| \} dt \right. \tag{9}$$

where, N_{load} is the load conditions and ω is the speed deviation of the generators. The proposed technique is applied to TAFM system. Two PSSs with different

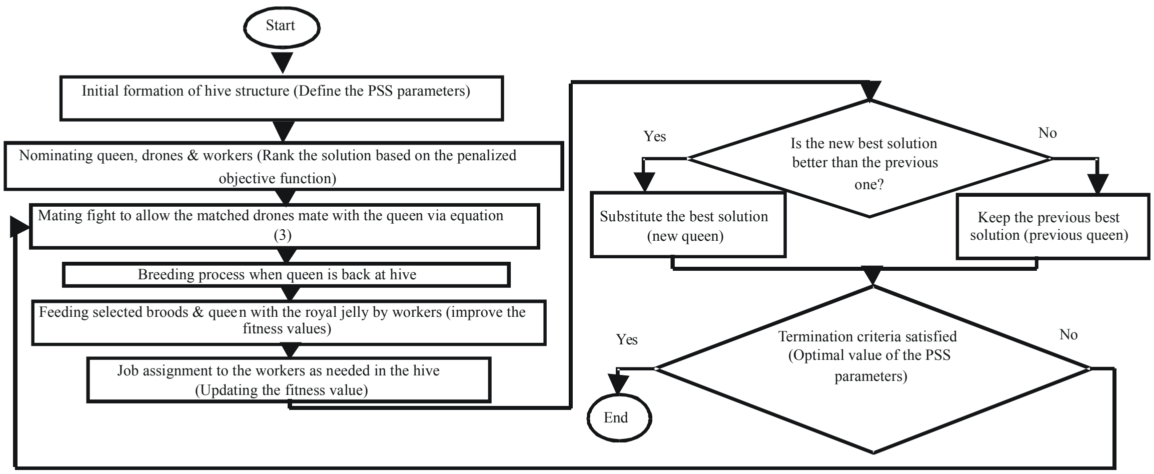

Fig. 1: Algorithm and computational flowchart of HBMO

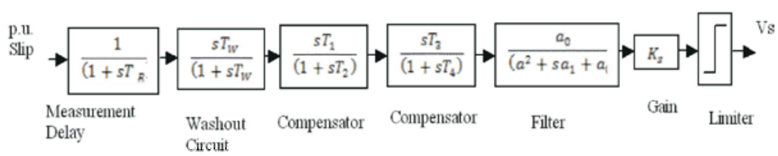

Fig. 2: The Block Diagram of PSS

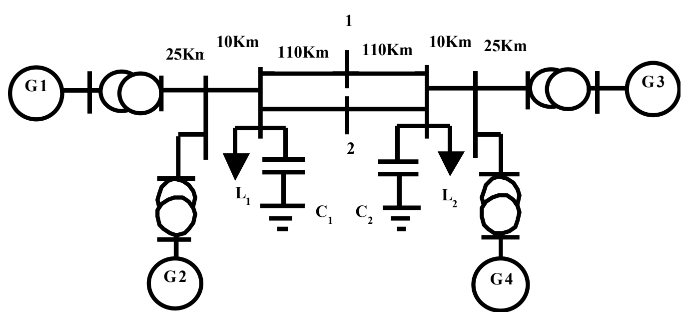

Fig. 3: TAFM system

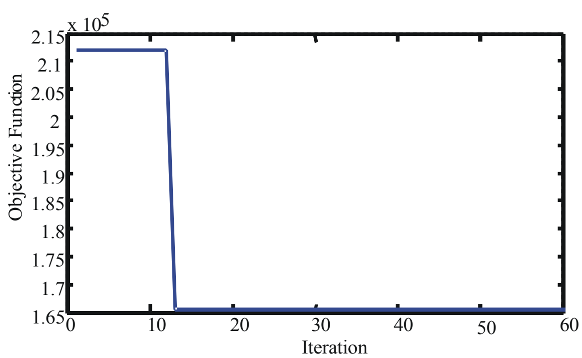

Fig. 4: Objective function variation of PSSs location

settings are installed at G2 and G4 while G1 and G3 are left without PSS. However in [11], the best location of PSSs is indicated in G1 and G4 with similar setting. Anyway, G2 and G4 are the best locations for installation of the PSSs in this paper, providing a suitable discrimination between very good and moderately good PSS settings [23]. Fig. 4 shows the trend of objective function's variation. Also the results of optimum parameters of PSSs and the parameters which are used to compare are presented in Table 3.

Also this algorithm has been applied to search for optimal settings of the proposed stabilizers. The convergence rate of the objective function f with the number of iterations is shown in Fig. 5. It is worth mentioning that the optimization process has been carried out with the system operating at nominal loading condition. For this step assumed that V_{SMax}= 0.15.

The proposed technique is applied here for the design of stabilizers for 4-generator system compared with [17]. The final settings of the optimized parameters for the proposed stabilizers are given in Table 4.

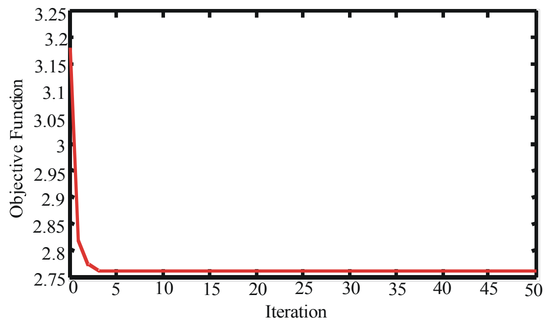

Fig. 5: Objective function variation of PSSs design

Table 1: Cpss Limitations in Case 1

Parameters	T_1	T_2	T_3	T_4	V_{SMax}	K_{pss}
Lower limit	0.01	0.01	0.01	0.01	0.05	10
Uper limit	1	1	10	10	0.5	100

Table 2: Cpss Limitations in Case 2

Parameters	T_1	T_2	T_3	T_4	K_{pss}
Lower limit	0.01	0.1	0.01	0.1	1
Uper limit	1	0.1	1	0.1	50

Table 3: Optimal Psss' Parameters of Tafm System

Methods		K_{pss}	T_1	T_2	T_3	T_4	V_{SMax}
HBMO	G2	41	0.001	0.002	8.4	11.8	0.36
	G4	40	0.002	0.002	9.1	12.6	0.37
SPEA	G1	45	0.26	0.01	4.2	10	0.33
	G4	45	0.26	0.01	4.2	10	0.33
GA	G1	100	0.52	0.04	0.65	5.8	0.31
	G4	100	0.52	0.04	0.65	5.8	0.31

Table 4: Optimal Settings of the Controller Parameters of the Proposed Scheme

Parameters	K_{pss}	T_1	T_2	T_3	T_4
G1	20.066	0.4020	0.6975	9.9241	4.9591
G2	21.105	0.3426	0.6887	9.0393	4.6446
G3	22.5	0.3825	0.5191	9.6731	4.6753
G4	21.6	0.3721	0.6991	9.54	4.0432

Simulation Results: The performance of the proposed robust HBMO Power System Stabilizer (HBMOPSS) is evaluated by applying a large disturbance to TAFM system consist of two scenarios as:

Scenario 1: In this scenario two optimum located PSSs are installed to G2 and G4. To investigate the performance of the PSSs under fault conditions, 9-cycle three phase fault ground fault at bus 1 cleared without equipment have been applied to the robustness of the controllers [10, 23]. Fig. 6 shows the variations of ω for generators in nominal operating condition. Fig. 7 and Fig. 8 show the system variations in light and heavy operation condition respectively. All of these figures present large signal stability of the test system with optimum PSSs. Also it is clear that, HBMO PSSs has a better performance rather than the other controllers compared with [11].

Scenario 2: In this which is compared with QFT technique [11], four PSSs are installed to proposed system. Time responses of the resulting closed-loop system with all four generators fitted with stabilizers were simulated for various disturbances and operating conditions. Fig. 9 shows the response of the system with all generators fitted with stabilizers and at nominal operating condition to a small impulse disturbance in the voltage reference of generator 1. Furthermore Fig. 10 and Fig. 11 shows the response of the system at light and heavy operating condition to the proposed disturbance respectively.

Case Study 2

New England Power System: In this study, the 10-machine 39-bus power system shown in Fig. 12 is considered. 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 loading are considered. Details of the system data and operating condition are given in Ref. [18].

Applying HBMO Algorithm to New England System: The problem of setting the parameters and locations of PSSs that assure maximum damping performance is solved using a HBMO optimization procedure with an eigenvalue-based performance index. In [18], the best location of PSSs is indicated in G5, G7 and G9. However, G3, G8 and G9 are the best locations for installation of the PSSs in this research, providing a suitable discrimination between very good and moderately good PSS settings. Fig. 13 shows the trend of objective function's variation and the information of algorithm is shown in Table 5.

For all operating conditions, the power system can be modeled by a set of nonlinear differential equations as:

$$\dot{x} = f(x,u) \tag{10}$$

where x is a vector of state variables $x = [\delta, \omega, E_q^{/}, \psi_d^{/}, E_d^{//}, \psi_q^{//}]$ and u is the vector of the PSS output signals. The system in Eq. (7) is then linearized around an equilibrium operating point of the power system. First, Eqs. (8) and (9) describe a linear model of the power system:

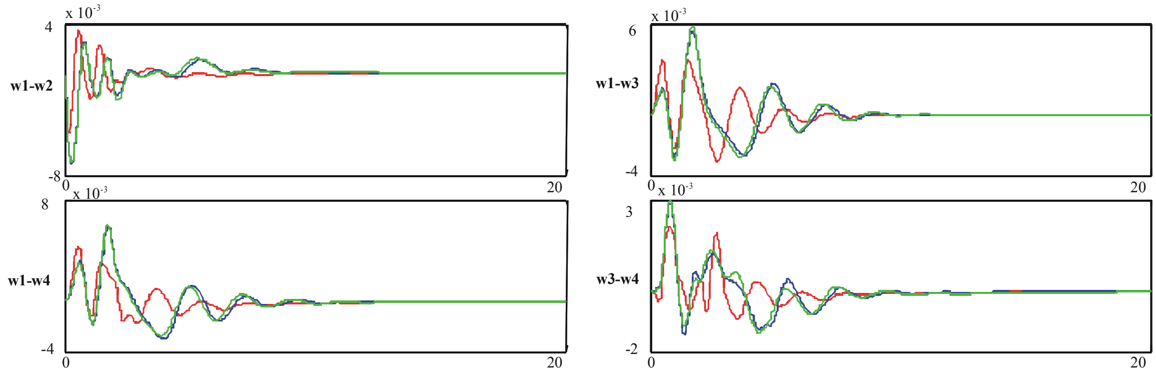

Fig. 6: System response under scenario 1 with nominal loading conditions: Solid (HBMOPSS) Dashed (SPEAPSS) Doted (GAPSS)

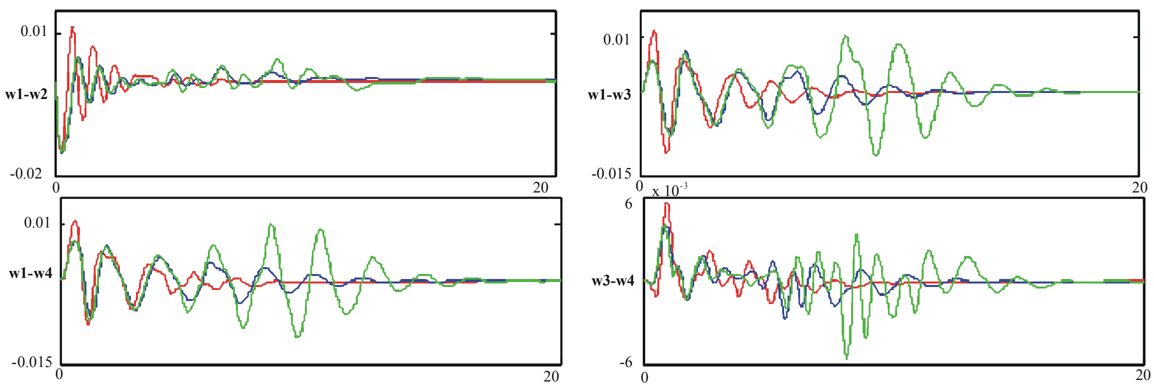

Fig. 7: System response under scenario 1 with light loading conditions: Solid (HBMOPSS) Dashed (SPEAPSS) Doted (GAPSS)

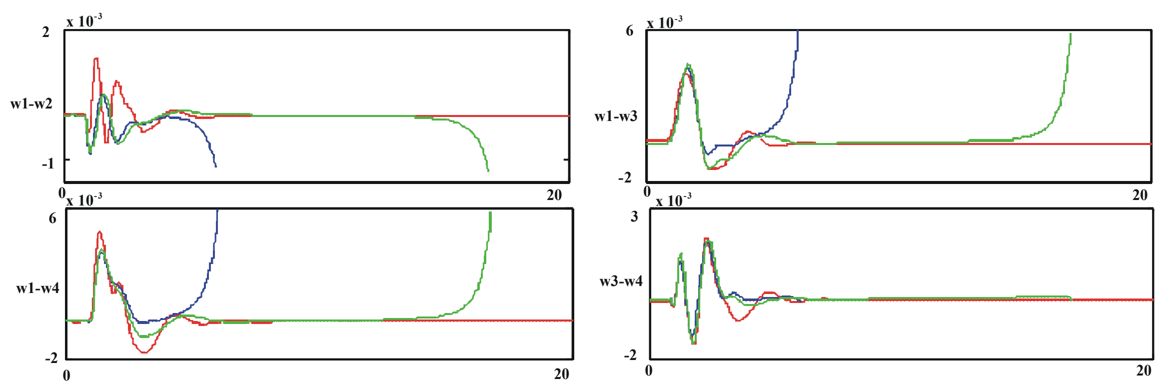

Fig. 8: System response under scenario 1 with heavy loading conditions: Solid (HBMOPSS) Dashed (SPEAPSS) Doted (GAPSS)

$$\dot{x} = Ax + Bu \tag{11}$$

$$y = Cx + Du \tag{12}$$

In the frequency domain, the transfer function associated with Eqs. (7) and (8) is given by:

$$P(s) = C(sI - A)^{-1} B + \mathrm{FD} \tag{13}$$

where, the poles of P(s) correspond to the eigenvalues of matrix A. The PSSs (controllers) are a lead–lag type and can be described as the diagonal matrix K(s):

$$u(s) = K(s)e(s) \tag{14}$$

Eq. (5) (above) can be expressed as:

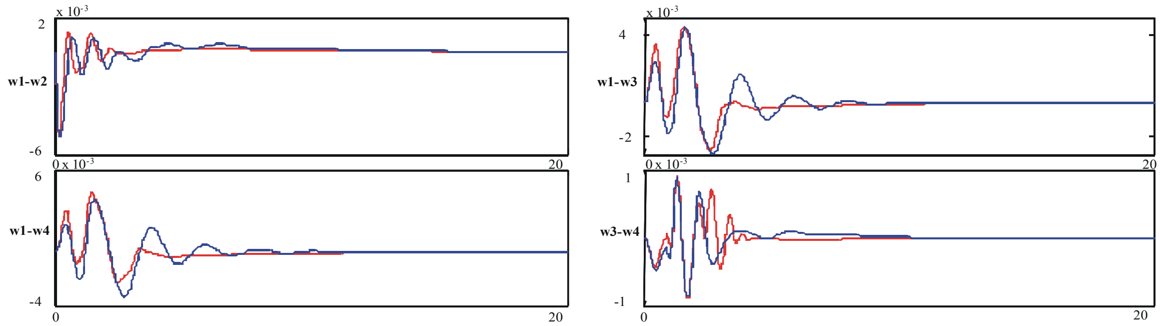

Fig. 9: System response under scenario 2 with nominal loading conditions: Solid (HBMOPSS) Dashed (SPEAPSS) Doted (GAPSS)

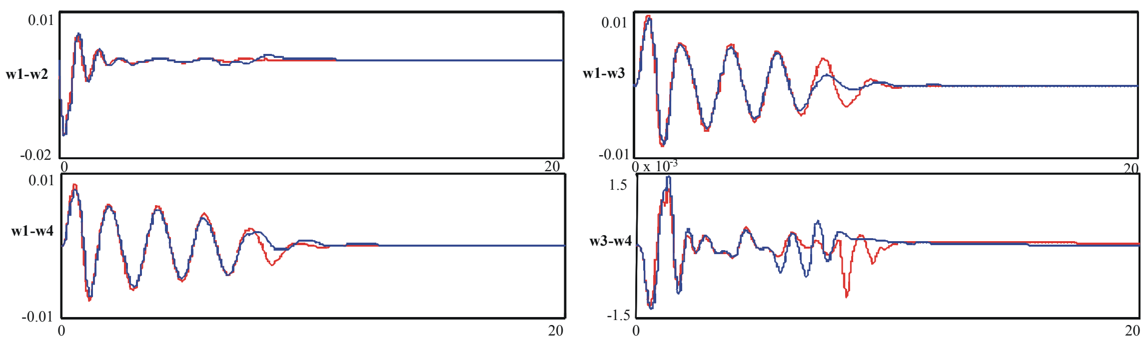

Fig. 10: System response under scenario 2 with light loading conditions: Solid (HBMOPSS) Dashed (SPEAPSS) Doted (GAPSS)

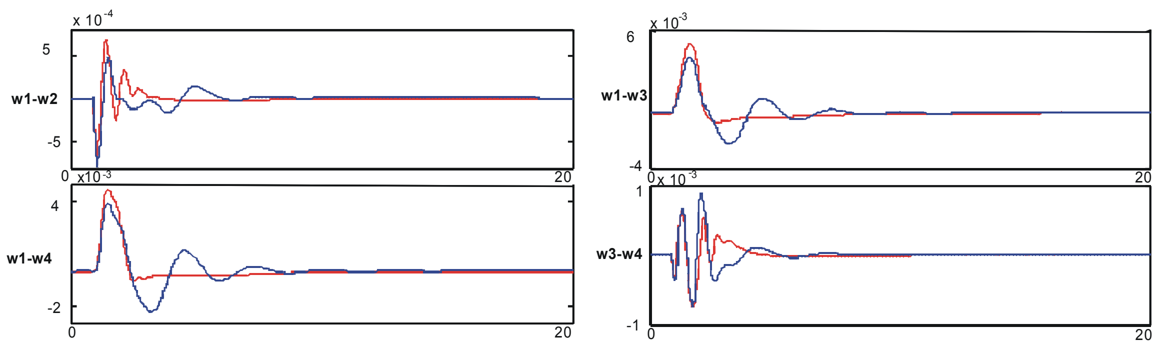

Fig. 11: System response under scenario 2 with heavy loading conditions: Solid (HBMOPSS) Dashed (SPEAPSS) Doted (GAPSS)

$$\dot{x}_k = A_k x_k + B_k e$$
$$V = C_k x_k + D_k e \tag{15}$$

where, x_k is the state vector of controllers. Combining Eq. (6) with Eqs. (2) and (3) a closed loop system is obtained.

$$\dot{x}_{cl} = A_{cl} x_{cl} \tag{16}$$

where $\dot{x}_{cl} = \begin{bmatrix} x \\ x_{cl} \end{bmatrix}$ is the state vector of the closed loop system. Let $\lambda j = \sigma_j \pm i\omega_j$ be the j-th eigenvalues (mode) of the closed loop system in Fig. 1. Then, the damping coefficient (ζ j) of the j-th eigenvalues is define with the following equation:

$$\xi_j = \frac{-\sigma_j}{\sqrt{\sigma_j^2 + \omega_j^2}} \tag{17}$$

Hence, the numerical results of ITAE, FD and ζ are presented in Table 6.

Simulation Results: The performance of the proposed robust HBMO Power System Stabilizer (HBMOPSS) is evaluated by applying a large disturbance to New England system consist of two scenarios as:

Table 5: Parameters of Algorithm in Case 2

Iteration	200
Capacity of Queen Sperm	15
Number of Worker	30
Number of Child	10
Number of Drone	300
Factor for Generate Child	0.86
Factor for Mutation	0.91
Factor for Reduce Speed Queen	0.98
Initial Speeds of Queen	1
End of Energy and Speed	0.1

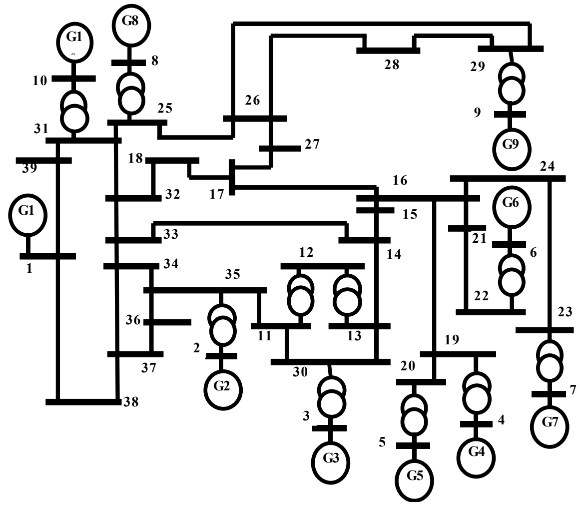

Fig. 12: Ten-machine 39-bus New England power system

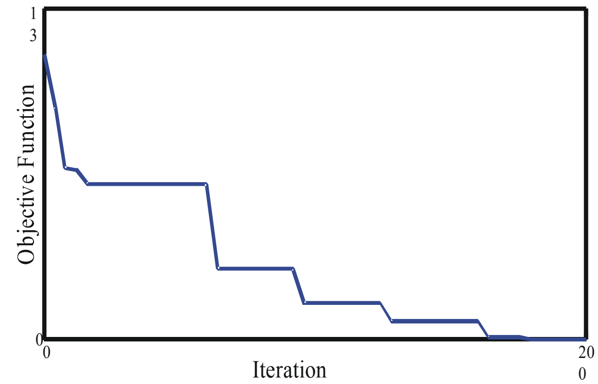

Fig. 13: Objective function variation of PSSs location and design

Scenario 1: In this scenario, performance of the proposed controller under transient conditions is verified by applying a 3-cycle three-phase fault at t=1 sec, on bus 25 at the end of line 25-26. The fault is cleared by permanent tripping the faulted line. Speed deviations of the generators G3, G8 and G9 under nominal, heavy and light load condition are shown in Fig. 14 respectively. It can be seen that the overshoot, undershoot, settling time and speed deviations of all machines are greatly reduced by applying the proposed GA-PSO based fuzzy PSSs.

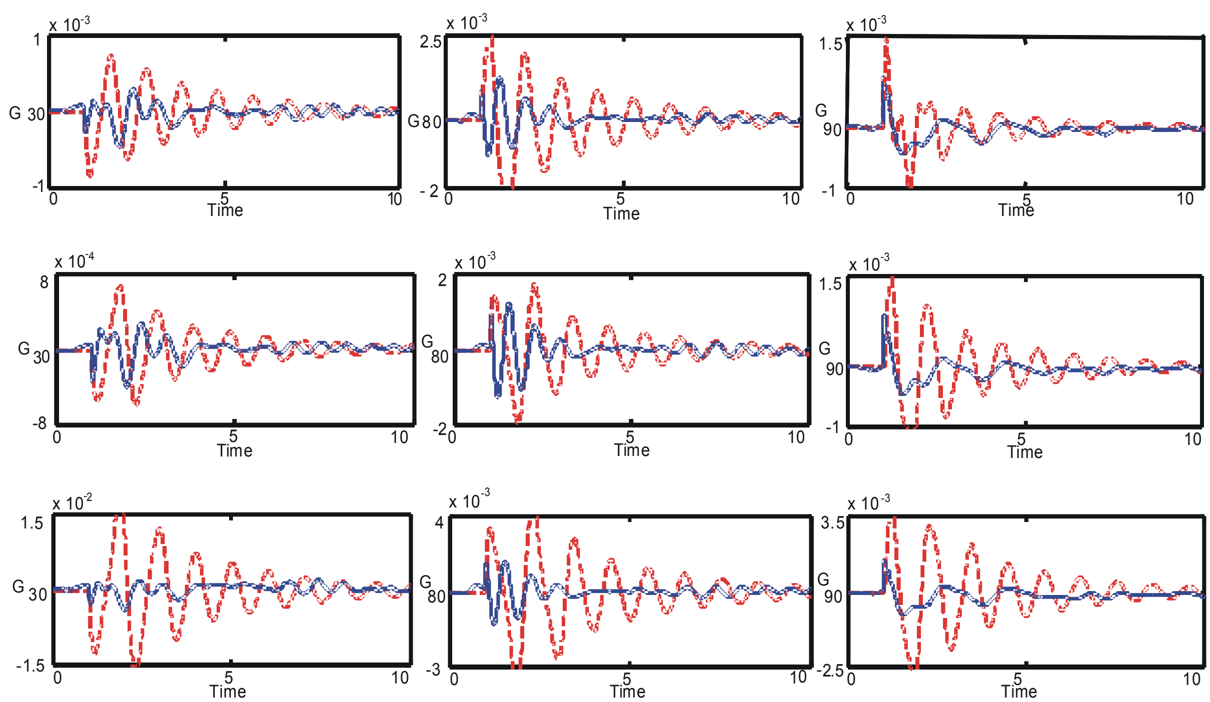

Fig. 14: System response under scenario 1 with nominal, light and heavy loading conditions, respectively: Solid (HBMOPSS) Dashed (TSPSS)

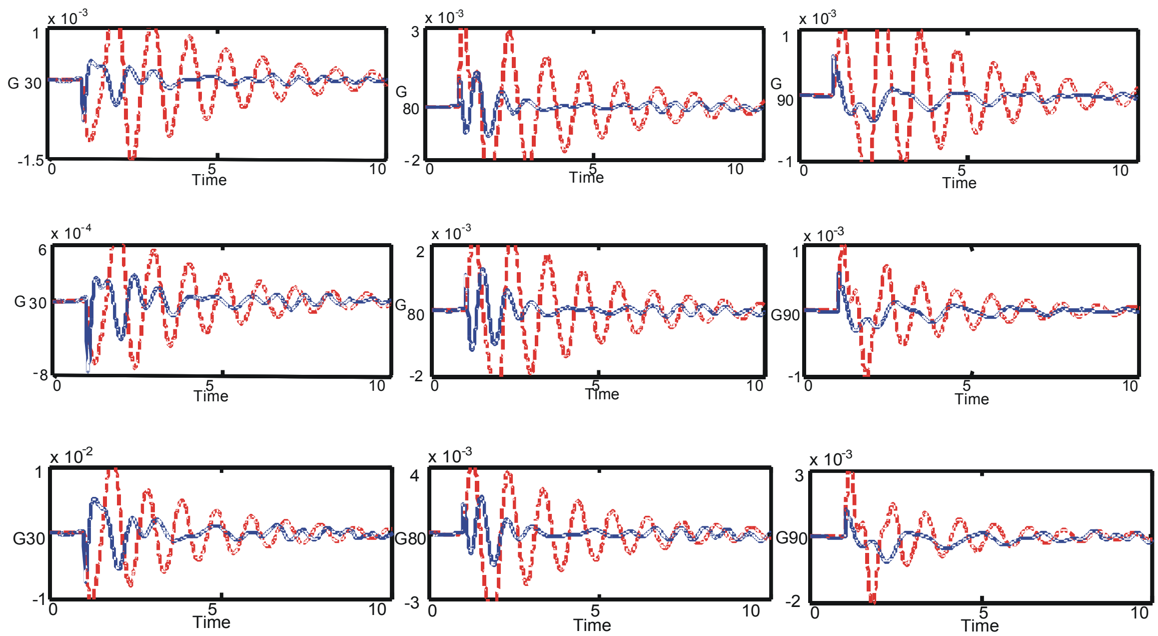

Fig. 15: System response under scenario 2 with nominal, light and heavy loading conditions, respectively: Solid (HBMOPSS) Dashed (TSPSS)

Table 6: PSSs parameters and locations set obtained by the proposed method in Case 2

No. of PSS	PSS Values	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	ITAE	FD	ζ
3	K_{pss}			9.062					9.085	8.726		0.0275	420.7	0.4359
	T_1			0.071					0.102	0.088				
	T_2			0.022					0.0227	0.022				
	T_3			0.051					0.092	0.086				
	T_4			0.022					0.0227	0.022				
4	K_{pss}		9.132	8.605			7.182			10.34		0.0268	585.3	0.2037
	T_1		0.345	0.103			0.585			0.211				
	T_2		0.022	0.022			0.0227			0.022				
	T_3		0.065	0.042			0.056			0.073				
	T_4		0.022	0.022			0.0227			0.022				
5	K_{pss}			6.632	5.905			7.802		10.01	9.531	0.0212	536.2	0.2410
	T_1			0.115	0.143			0.125		0.201	0.218			
	T_2		0.0227	0.022	0.022	0.0227	0.0227	0.022	0.0227	0.022	0.022			
	T_3			0.018	0.010			0.057		0.043	0.076			
	T_4		0.0227	0.022	0.022	0.0227	0.0227	0.022	0.0227	0.022	0.022			
6	K_{pss}		6.132	7.705		8.802		10.81	9.615	8.082		0.0191	386.6	0.4359
	T_1		0.102	0.113		0.105		0.121	0.118	0.485				
	T_2		0.0227	0.0227	0.0227	0.0227	0.0227	0.022	0.0227	0.022	0.0227			
	T_3		0.014	0.020		0.047		0.056	0.098	0.016				
	T_4		0.022	0.022	0.0227	0.0227	0.0227	0.022	0.0227	0.022	0.0227			
7	K_{pss}		8.182	9.745		8.852	11.85		10.95	9.882	8.192	0.027	394.5	0.733
	T_1		0.135	0.165		0.187	0.131		0.192	0.342	0.674			
	T_2		0.022	0.022	0.0227	0.022	0.0227	0.0227	0.0227	0.022	0.022			
	T_3		0.023	0.025		0.081	0.031		0.072	0.044	0.054			
	T_4		0.022	0.022	0.0227	0.0227	0.0227	0.0227	0.0227	0.022	0.022			
8	K_{pss}	9.92	10.2		11.21	12.32	9.432	9.811	12.32	10.52		0.0113	273.6	0.7330
	T_1	0.231	0.251		0.132	0.154	0.127	0.459	0.438	0.218				
	T_2	0.022	0.022	0.0227	0.022	0.022	0.0227	0.022	0.0227	0.022	0.0227			
	T_3	0.051	0.081		0.076	0.043	0.098	0.021	0.054	0.072				
	T_4	0.022	0.022	0.0227	0.022	0.022	0.0227	0.022	0.0227	0.022	0.0227			

Table 6: Continued

9	K_{pss}		9.109	7.905	6.531	7.629	11.21	5.876	12.023	5.296	8.178	0.0323	382.9	0.7330
	T_1		0.191	0.242	0.264	0.245	0.258	0.207	0.2278	0.263	0.25			
	T_2		0.022	0.022	0.022	0.022	0.022	0.022	0.0227	0.022	0.022			
	T_3		0.062	0.071	0.070	0.016	0.048	0.071	0.0813	0.024	0.032			
	T_4		0.022	0.022	0.022	0.022	0.022	0.022	0.0227	0.022	0.022			
10	K_{pss}	9.109	7.905	6.531	7.629	6.216	5.876	6.023	5.296	7.178	9.178	0.0051	243.5	0.3436
	T_1	0.291	0.242	0.164	0.145	0.158	0.207	0.227	0.163	0.150	0.230			
	T_2	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.0227	0.022	0.022			
	T_3	0.062	0.071	0.070	0.116	0.048	0.071	0.081	0.024	0.032	0.032			
	T_4	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.0227	0.022	0.022			
[TS]	K_{pss}					12.25		10.98		19.75		0.1057	1699.5	
	T_1					0.664		0.655		0.203				
	T_2					0.022		0.022		0.022				
	T_3					0.345		0.563		0.06				
	T_4					0.022		0.022		0.022				

Scenario 2: 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. Figs. 15 shows the result of G3, G8 and G9 under nominal, heavy and light load condition respectively.

Also to demonstrate performance robustness of the proposed method, the Integral of the Time multiplied Absolute value of the Error (ITAE) and Figure of Demerit (FD) based on the system performance characteristics are defined as [24]:

$$ITAE = \int_0^{t_{sim}} \left| \sum_{i=1}^{N_g} \omega_i \right| .dt \tag{18}$$

$$FD = \sum_{i=1}^{N_g} ((\left|\max(\omega_i)\times 5000\right|)^2 + (\left|\min(\omega_i)\times 10000\right|)^2 + 0.1\times T_{sGi}^2)$$

where, Overshoot (OS), Undershoot (US) and settling time of rotor angle deviation of one machine is considered for evaluation of the FD. It is worth mentioning that the best state for PSSs in case 2 are G3, G8 and G9 according to numerical results which are presented in Table 6. It can be seen that the values of these system performance characteristics with the proposed controller are much smaller compared to that TSPSS. This demonstrates that the overshoot, undershoot settling time and speed deviations of all machines are greatly reduced by applying the proposed HBMO technique.

CONCLUSION

In this research, a method of CPSS design named Honey Bee Mating Optimization (HBMO) is introduced for power system stabilizers design and location. HBMO algorithm proposed in this paper is easy to implement without additional computational complexity. Also the convergence speed of this algorithm is better. The described algorithm allow simultaneously tuning of PSSs and finding out their optimal locations in TAFM system. The effectiveness of the proposed method is tested on two case studies as; 4 machine 10 buses Kundur's system and 10-machine 39-buse New England Power System for a wide range of load demands and disturbances under different operating conditions. The proposed method is compared with SPEA, AG and QFT for case 1 and compared with TS through FD, ITAE and æ performance indices under different operating condition for case 2. The simulation results confirm that the proposed HBMOPSS can work effectively over a wide range of loading conditions. The proposed method demonstrates its superiority in computational complexity, success rate and solution quality and following conclusions can be drawn about the proposed method.

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