International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

September 2013	Issue 16	Volume 5	Number 3	Pages 109-117

HYBRID ARTIFICIAL NEURAL NETWORK AND HONEY BEE MATING OPTIMIZATION BASED ON OPTIMAL POWER SYSTEM STABILIZER IN MULTIMACHINE ENVIRONMENT

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Abstract- A Hybrid technique of Artificial Neural Network and Honey Bee Mating Optimization (H-ANN-HBMO) is presented in this paper to damp power system oscillation in multi machine environment. By considering this strategy the weights of ANN is optimized to find the optimum work point of controller. The proposed strategy consists of an ANN controller, which is used as a power system stabilizer in power system to damp the received signal from generator and the HBMO technique for tuning the ANN parameters. The proposed method has the features of a simple structure, adaptive and fast response. In proposed syndicate tuning technique, three performances indicate as ITAE and FD is computed for stability and performance at each of given set of operating conditions of the system. This newly proposed controller is more efficient because it cope with oscillations and different operating points. The effectiveness of proposed controller is tested in two case studies. The first one is single machine infinite bus system and second case study is 10-machine New England power system.

Keywords: ANN, Power System, PSS, Multi-Machine.

I. INTRODUCTION

Some of the earliest power system stability problems included spontaneous power system oscillations at low frequencies. These Low Frequency Oscillations (LFOs) are related to the small signal stability of a power system and are detrimental to the goals of maximum power transfer and power system security. Once the adjustment of using damper windings on the generator rotors and turbines to control these oscillations was found to be satisfactory, the stability problem was thereby disregarded for some time [1].

However, as power systems began to be operated closer to their consistency limits, the weakness of a synchronizing torque among the generators was distinguished as a major cause of system instability [2]. Automatic Voltage Regulators (AVRs) helped to improve the steady-state stability of power systems, but transient stability started a concern for the power system operators.

With the development of large, interconnected power systems, another concern was the transfer of large amounts of power across extremely long transmission lines. The addition of a supplementary controller into the control loop, such as the introduction of power system stabilizers (PSSs) to the AVRs on the generators, supplies the means to reduce the inhibiting effects of low frequency oscillations [3]. Most of the time the PSSs and AVRs are locally controlled, which means that, the controller is designed to act on measurements such as bus voltage, generator shaft speed, or rotor angle of the associated machine's controls as presented in Figure 1.

Recently, PSSs. Conventionally lead-lag control is the old, traditional methods, which has fixed structure and designed by a linear model obtained by linearizing nonlinear model around a nominal operating point to provide the optimum performance for the nominal operating condition and system parameters [4-5] has proposed several methods for damping the oscillation in power system.

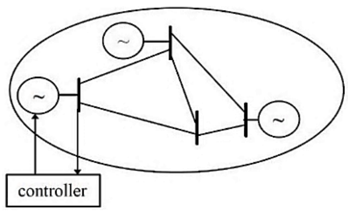

Figure 1. Local feedback controller

Although, this method satisfy the stability of system in some work points but, the main problem encountered in the Conventional PSS (CPSS) design is the power system constantly experiences changes in operating conditions due to variation in generation and load patterns, as well as changes in transmission networks. Therefore, the achieved results of this technique present poor dynamic performance [6]. To overcome these problems, a number of techniques have been developed for designing PSSs, recently. Intelligent optimization based methods have been initiated to solve this problem.

Two main techniques used for the parameter tuning of the PSS in the power system are sequential tuning and simultaneous tuning. To find a set of optimal PSS parameters under different operating conditions, the tuning, and analyzing of PSS parameters must be repeated over different operating conditions of the system [7]. The simultaneous tuning of PSS parameters is commonly formulated as a very large scale, nonlinear, non-differentiable optimization problem. The mentioned optimization problem is difficult to solve by applying traditional differentiable optimization algorithms. Sequential quadratic programming (SQP) techniques are fast deterministic optimization techniques [8], but they are very sensitive to the choice of initial point.

To overcome the abovementioned problems, many random search methods such as Tabu search (TS) [9], Simulated Annealing (SA) [10], Ant Colony Optimization (ACO) [11] and Harmony Search (HS) [12], Evolutionary Programming (EP) [13], Bacteria Foraging Optimization (BFO) [14], Genetic Algorithm (GA) [15], and Particle Swarm Optimization (PSO) [16-17] have been used. To find an appropriate solution through robust control with good accuracy, this paper proposed a hybrid technique with the combination of Honey Bee Mating Optimization (HBMO) and Artificial Neural Network (ANN).

According to the advantages of the mentioned techniques, this newly proposed technique play fast controller role in multi-machine power system by damping the oscillation in different operation condition. The effectiveness of the proposed technique is applied over two test cases as, single machine infinite bus system which is compared with SPEA and GA [18], and 10 machine 39 buses New England power system with the comparison by PSO and CPSS [19]. The obtained numerical results demonstrate that proposed technique is effective and alternative to other compared techniques.

II. PROBLEM STATEMENT

The complex nonlinear model related to an *n*-machine interconnected power system, can be described by a set of differential algebraic equations by assembling the models for each generator, load, and other devices such as controls in the system, and connecting them appropriately via the network algebraic equations. The synchronous machine is the most important part of power systems and 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 for this paper [20]. Figure 2 shows the place of fuzzy controller in the power systems as a PSS [1].

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

$$\dot{\omega}_i = (P_{mi} - P_{ei} - D_i(\omega_i - 1)) / M_i \quad (2)$$

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

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

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

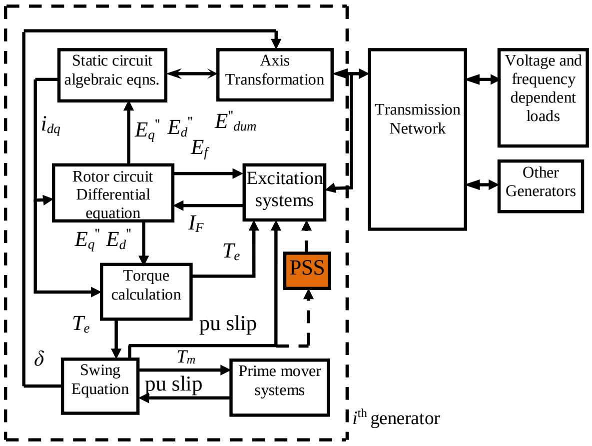

Figure 2. Structure of PSS in power systems [1]

III. INTELIGENT CONTROL STRATEGY

A. Honey Bee Mating Optimization

The honeybee 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 beehive. 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 [21]. 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 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 [22]:

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

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)), S (t) is speed of 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:

$$S(t+1) = \alpha \times s(t)(2) \qquad (7)$$

$$E(t+1) = E(t) - \gamma \qquad (8)$$

where, α is a factor and γ is the amount of energy reduction after each transition. In addition, Algorithm and computational flowchart of HBMO method to optimize the PSS parameters is presented in Figure 3 [22].

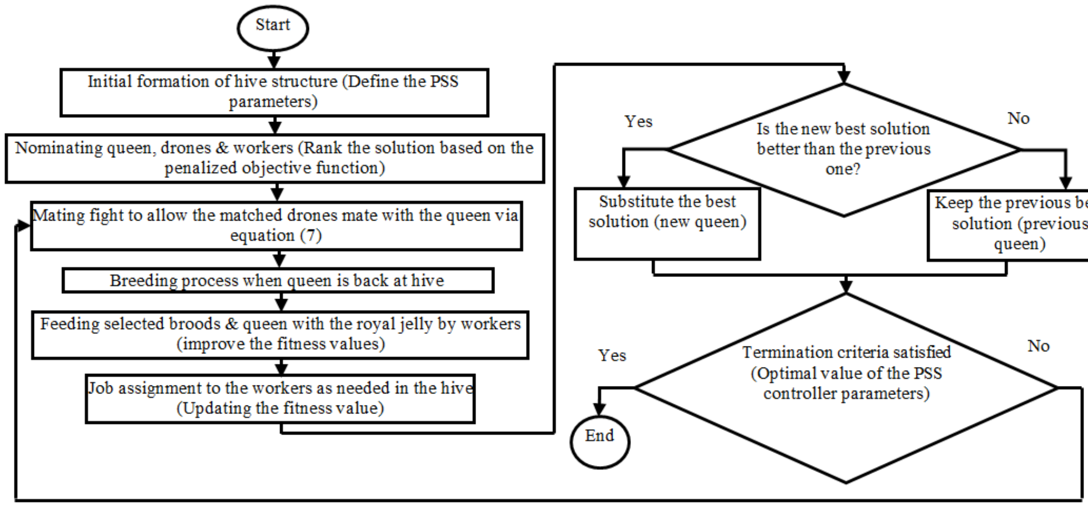

Figure 3. Algorithm and computational flowchart of HBMO [22]

Thus, HBMO algorithm may be constructed with the following five main stages [23]:

1. 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
2. Creation of new broods by crossoverring the drones genotypes with the queen's
3. Use of workers (heuristics) to conduct local search on broods (trial solutions)
4. Adaptation of workers fitness based on the amount of improvement achieved on broods.
5. Replacement of weaker queens by fitter broods

B. Artificial Neural Network

The increasing prominence of the computers has led to a new way of looking at world. Artificial Neural Networks (ANN) and HBMO are considered as so called soft computing methods are now a days becoming predominant tools in area of Artificial Intelligence linked application oriented methods. The Neural network theory was first adopted in 1940 where starting point was the learning law presented by ITEBB in 1949, where demonstrated how neurons could exhibit learning behavior [24].

The application further waxed and waned away because of lack of powerful technological advancement. The resurgence occurred recently due to the new methods that are emerging as well as the computational power suitable for simulation of interconnected neural networks [25].

Further to the technological advancement in the field of ANN, researchers were attracted on their important applications where logical and relational thinking is required. Among the major applications viz., robotics, analysis, optimal control, database, learning, signal processing, semiconductors, power system related applications became a useful tool for the online researchers in this field.

ANN is biologically inspired and represented as a major extension of computation. They embody computational paradigms, based on biological metaphor, to mimic the computations of brain [26]. The improved understanding of the functioning of neuron and the pattern of its interconnection has enabled researchers to produce the necessary mathematical model for testing their theories and developing practical applications.

Main applications of the ANN's can be divided into two principal streams. The first stream among this is concerned with modeling the brain and thereby explains its cognitive behavior. The primary aim of researchers in the second stream is to construct useful 'computers' for real world problems of classification or Pattern Recognition by drawing on these principles.

B.1. Definition of the Neural Network

Neural networks are systems that typically consist of a large number of simples processing units, called Neurons. A neuron has generally a high-dimensional Input vector and one single output signal. This output signal is usually a non-linear function of the input vector and a weight vector.

The function to be performed on the Input vector is hence defined by the non-linear function and the weight vector of the neuron. The weight vector is adjusted in a training phase by using a large set of examples and the learning rate. The learning rule adapts the weight of all neurons in networks in order to learn an underlying relation in the training example.

B.2. Artificial Neural Network Fundamentals

Elementary processing unit of ANN's is neuron. Generally it contains several inputs but has only one output. The main differences between various existing models of ANN are mainly in their architectures or the way their basic processing elements (neurons) are interconnected. As basic element, the neurons are not powerful but their interconnections allow encoding relationship between variables of the problems to which it is applied and providing very powerful processing capabilities. General model of the processing unit of ANN can be considered to have the following three elements [27]. Figure 4 shows the schematic diagram of the neuron.

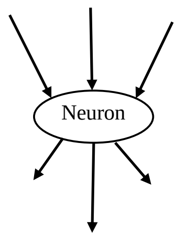

Figure 4. Schematic Diagram of the Neuron

In this paper the presented weights are optimized by HBMO. So descriptions of weights are presented in below.

C. Weighted Summing Unit

The weighted summing unit consists of external or internal inputs X_i (x_1, x_2, x_3, …, x_n) times the corresponding weights W_{ij} = (w_{i1}, w_{i2}, ... w_{in}). The fixed weighted inputs may be either from the previous layers of ANN or from the output of neurons. If these inputs are derived from neuron outputs, it forms feedback architecture it has feed forward architecture [28].

D. Linear Dynamical Function

It is essentially a single input or single output function block. This block may exist for time varying signals and introduces a function that is an integral, a proportional, a time delay or a combination of these. For example, following two general functions can be used to relate input P_i with output Q_i as:

$$\left(a_1, a_2\right) Q_i\left(t\right) = P_i\left(t\right) \tag{9}$$

$$Q_i\left(t\right) = P_i\left(t - T\right) \tag{10}$$

E. Nonlinear Function

This decides the firing of neuron for a given input values. It is a static nonlinear function, which may be pulse type or step type, differentiable (smooth) or non-identification (sharp) and having positive mean or zero mean. Some of the examples of such functions are threshold, sigmoid, Tan hyperbolic or Gaussian functions. Different characteristics of neurons can be evolved using different type and combination of the above three of its basic components.

- Perception models consist of weighted summing unit having no feedback inputs, no dynamic function, and signal as nonlinear function.
- Feedback or dynamic networks utilize the dynamic function block.

In this paper, a multi-layer feed-forward neural network is applied. Major application of feed-forward neural network is in large-scale systems that contain a large number of variable and complex systems where little analytical knowledge is available. Figure 5 shows the three layer of this application.

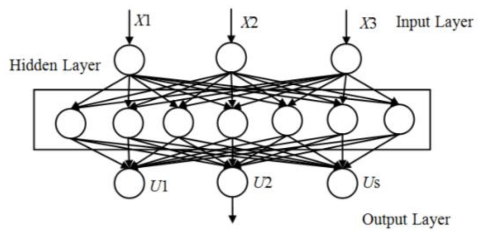

Figure 5. Three Layer feed-forward neural network

IV. HYBRID TECHNIQUE OVER TEST CASES

In this section, the proposed hybrid strategy is applied over two case studies in literature as,

A. Single-Machine Infinite Bus System

The first one is the single-machine infinite bus system considered for small-signal performance study, which is shown in Figure 6 [4]. The third-order model comprising of the electromechanical swing equation and generator internal voltage equation represents the generator.

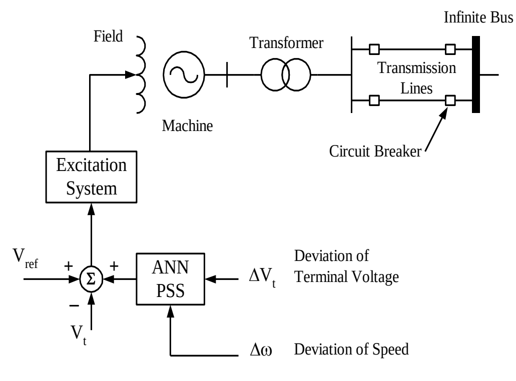

Figure 6. Schematic diagram of 1 machine infinite bus system and MOHBMOPSS [4]

B. New England Power System

The second case is the 10-machine 39-bus power system shown in Figure 7. To assess the effectiveness and robustness of the proposed method over a wide range of loading conditions, different operation conditions are considered. Details of the system data and operating condition are given in reference [19].

V. APPLYING MOHBMO TECHNIQUE TO POWER SYSTEM

A. Single-Machine Infinite Bus System Results

In this paper, three performance indices are considered as Demerit (*FD*) and Integral of the Time multiplied Absolute value of the Error (*ITAE*) for both case studies are presented, respectively.

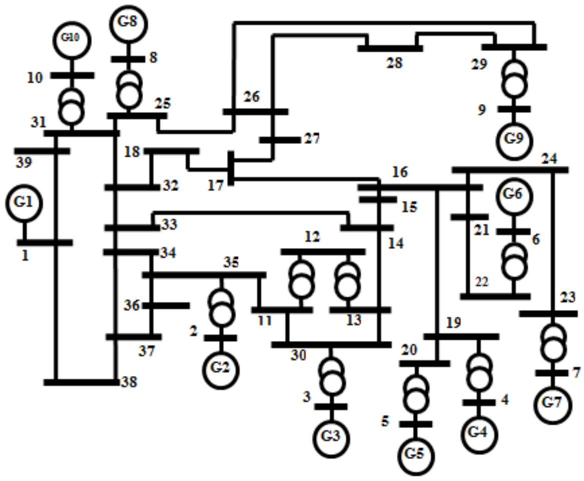

Figure 7. Ten-machine 39-bus new England power system [4]

It is very important that, the performance of the proposed controller be tested under transient conditions by applying a 6-cycle three-phase fault or increasing the mechanical torque. The simulation operated with hybrid HBMO-ANN are considered and compared with other techniques. The simulation results are presented in Figures 8 and 9.

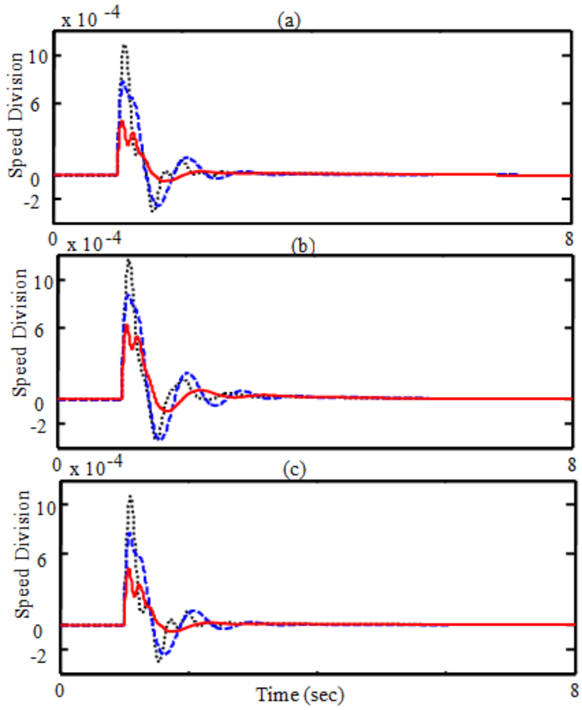

Figure 8. System response by 0.2 pu. step increasing the mechanical torque in t = 1, Solid (Proposed-PSS), Dashed (SPEA-PSS) Doted (GA-PSS), (a) P = 0.8, Q = 0.4, X_e = 0.3, (b) P = 0.5, Q = 0.1, X_e = 0.3, (c) P = 1.0, Q = 0.5, X_e = 0.3

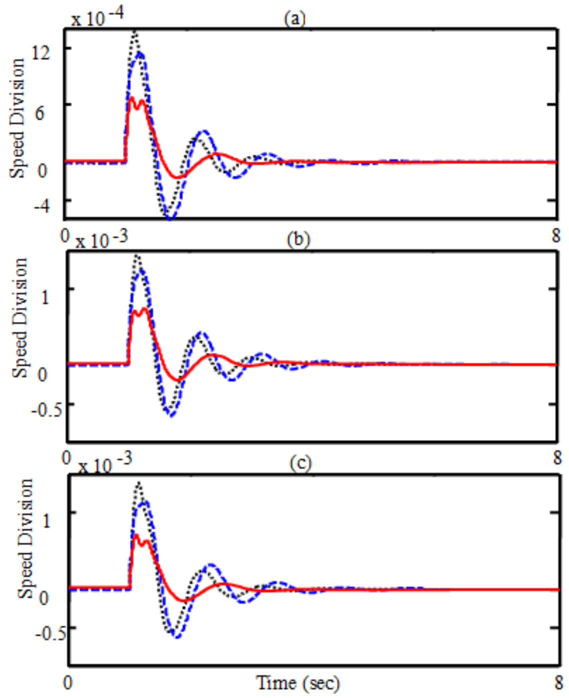

Figure 9. System response by 0.2 pu step increasing the mechanical torque in t = 1, Solid (Proposed-PSS), Dashed (SPEA-PSS) Doted (GA-PSS), (a) P = 0.8, Q = 0.4, X_e = 0.6, (b) P = 0.5, Q = 0.1, X_e = 0.6, (c) P = 1.0, Q = 0.5, X_e = 0.6

$$FD = \frac{\sum_{i=1}^{N_G} 10\times\left((500\times OS_i)^2+(8000\times US_i)^2+0.01\times T_{s,i}^2\right)}{N_G} \quad (11)$$

$$ITAE = 10\times\sum_{i=1}^{N_G}\int_0^{t_{sim}} t(|\Delta\omega_i|)dt \quad (12)$$

The details of load conditions are presented in Table 1 and the numerical results for these load conditions for *FD* and *ITAE* are presented in Table 2. It can be seen that the overshoot, undershoot, settling time and speed deviations of machine is greatly reduced by applying the proposed H-HBMO-ANN controller.

B. New England System Results

In this part, three scenarios are considered over the second case. Figure 10 shows the trend of HBMO convergence over weights in two case studies.

Table 1. Condition for compare simulation

Case No.	P	Q	X_e	H
1	0.8	0.4	0.3	3.25
2	0.5	0.1	0.3	3.25
3	1.0	0.5	0.3	3.25
4	0.8	0.4	0.6	3.25
5	0.5	0.1	0.6	3.25
6	1.0	0.5	0.6	3.25
7	0.8	0.0	0.6	3.25
8	1.0	-0.2	0.3	3.25
9	0.5	-0.2	0.6	3.25
10	1.0	0.2	0.3	0.81

Table 2. Calculate of *FD* and *ITAE* for 10 point with three faults in 1 sec

No.	H-HBMO-ANN		SPEA		GA	
	ITAE	*FD*	*ITAE*	*FD*	*ITAE*	*FD*
1	0.670	3.687	1.424	4.543	1.508	4.838
2	1.111	3.836	1.713	5.019	1.895	5.747
3	0.801	3.837	1.501	4.682	1.578	4.945
4	0.670	3.736	1.472	4.672	1.418	4.738
5	1.124	3.166	1.809	5.123	1.455	5.647
6	0.802	3.834	1.356	4.673	1.388	4.955
7	0.673	3.736	1.378	4.398	1.418	4.748
8	0.802	3.876	1.398	4.709	1.579	4.933
9	1.124	3.809	1.788	4.909	1.795	5.202
10	0.808	3.998	1.404	3.784	1.579	4.901

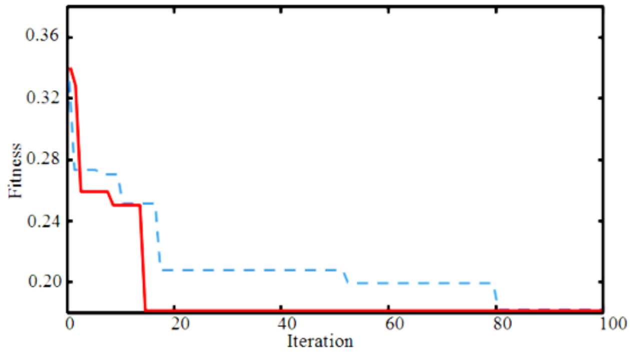

Figure 10. Trend of HBMO convergence over weights

Table 3. Calculate of *FD* and *ITAE* for different load changes

Change load	HBMO		PSO		CPSS	
	ITAE	*FD*	*ITAE*	*FD*	*ITAE*	*FD*
25%	3.5370	3.6498	4.0625	3.7832	8.4488	4.9543
20%	1.2992	2.5336	1.4169	2.5026	2.0137	2.8463
15%	0.8193	1.9142	0.9741	1.9912	1.3903	2.3726
10%	0.7441	1.6597	0.8588	1.7565	1.2431	2.1260
5%	0.6785	1.4409	0.7801	1.5277	1.1752	1.9497
Nominal	0.6216	1.3083	0.7106	1.3821	1.0574	1.8661
-5%	0.5745	1.2347	0.6521	1.3178	1.0049	1.8278
-10%	0.5732	1.2627	0.6597	1.2927	1.0378	1.8709
-15%	0.6877	1.4744	0.8019	1.6282	1.1271	2.1513
-20%	1.4966	2.3386	1.8361	2.4990	2.0636	2.8972
-25%	8.2929	3.8878	9.5537	3.9602	10.3716	4.8344

Table 4. Calculate of *FD* and *ITAE* for different load changes

Change load	HBMO		PSO		CPSS	
	ITAE	*FD*	*ITAE*	*FD*	*ITAE*	*FD*
25%	3.8818	1.5772	3.9355	1.6080	3.6569	1.6273
20%	1.3068	1.3882	1.4097	1.4092	1.3465	1.4904
15%	0.6135	1.0192	0.6741	1.0710	0.8902	1.3865
10%	0.5665	0.9507	0.6188	0.9851	0.8564	1.3499
5%	0.5597	0.9379	0.6074	0.9763	0.8535	1.3619
Nominal	0.5668	0.9453	0.6053	0.9873	0.8761	1.3635
-5%	0.5716	0.9605	0.6023	1.0054	0.8668	1.3719
-10%	0.5734	0.9023	0.5962	0.9608	0.8662	1.3857
-15%	0.6028	0.9453	0.6178	1.0048	0.8762	1.4063
-20%	0.7472	1.2391	0.7371	1.1980	0.9326	1.4354
-25%	3.5174	1.5012	3.5939	1.6231	2.2669	1.4812

- **Scenario 1**

It is very important that, the performance of the proposed controller be tested under transient conditions by applying a 6-cycle three-phase fault or increasing mechanical torque. Therefore, in this scenario a 6-cycle three-phase fault is applied in line 26-29 and bus 29. The responses of generators 2-10 are presented in Figure 11. In addition, the numerical results of *FD* and *ITAE* are presented in Table 3.

- **Scenario 2**

In this scenario, a 6-cycle three-phase fault is applied in line 26-29 and bus 29. Where, the system is come back to the stability status without omitting the error. The responses of generators 2-10 are presented in Figure 12 without omitting the line. In addition, the numerical results of *FD* and *ITAE* are presented in Table 4.

- **Scenario 3**

In this scenario a 0.1 step is applied over the torque of generators. The responses of generators 2-10 are presented in Figure 13 without omitting the line. In addition, the numerical results of *FD* and *ITAE* are presented in Table 5.

Table 5. Calculate of *FD* and *ITAE* for different load changes

Change load	HBMO		PSO		CPSS	
	ITAE	*FD*	*ITAE*	*FD*	*ITAE*	*FD*
25%	3.5654	1.2342	3.8689	1.5011	3.6947	1.3109
20%	0.4916	0.8103	0.5591	0.9978	0.7989	1.0382
15%	0.2007	0.6192	0.2327	0.6923	0.4571	1.0411
10%	0.2013	0.6092	0.2120	0.6271	0.4539	1.0117
5%	0.2091	0.5777	0.2122	0.6032	0.4771	1.0446
Nominal	0.2037	0.6037	0.2167	0.6069	0.5069	1.0488
-5%	0.2125	0.6099	0.2242	0.6178	0.5294	1.0551
-10%	0.2227	0.6326	0.2325	0.6373	0.5404	1.0621
-15%	0.2545	0.6849	0.2610	0.6993	0.5570	1.0726
-20%	0.4096	0.9194	0.4140	0.9358	0.7436	1.1157
-25%	2.3918	1.1977	2.6551	1.2324	4.6553	1.6898

VI. CONCLUSIONS

In this paper, a design scheme of robust PSS for single machine connected to an infinite bus and ten-machine New England power system using hybrid technique have been developed. So, the hybrid technique of Artificial Neural Network and Honey Bee Mating Optimization (H-ANN-HBMO) is presented to damp power system oscillation where the weights of ANN are optimized to find the optimum work point of controller. The proposed technique is tested in various load condition for the solution of the low frequency oscillation problem in power system. The single machine infinite bus system is compared with SPEA and robust PSS that is tuned by GA through the mentioned performance indicates. The second case study is compared with PSO and CPSS under different load conditions. The achieved numerical results of power systems demonstrate that the proposed strategy is superior to other compared methods.

NOMENCLATURES

δ: Rotor angle
ω: Rotor speed
P_m : Mechanical input power
P_e : Electrical output power
E'_q : Internal voltage behind x'_d
E_{fd} : Equivalent excitation voltage
T_e : Electic torque
T'_{do} : Time constant of excitation circuit
K_A : Regulator gain
T_A : Regulator time constant
v_{ref} : Reference voltage
v : Terminal voltage

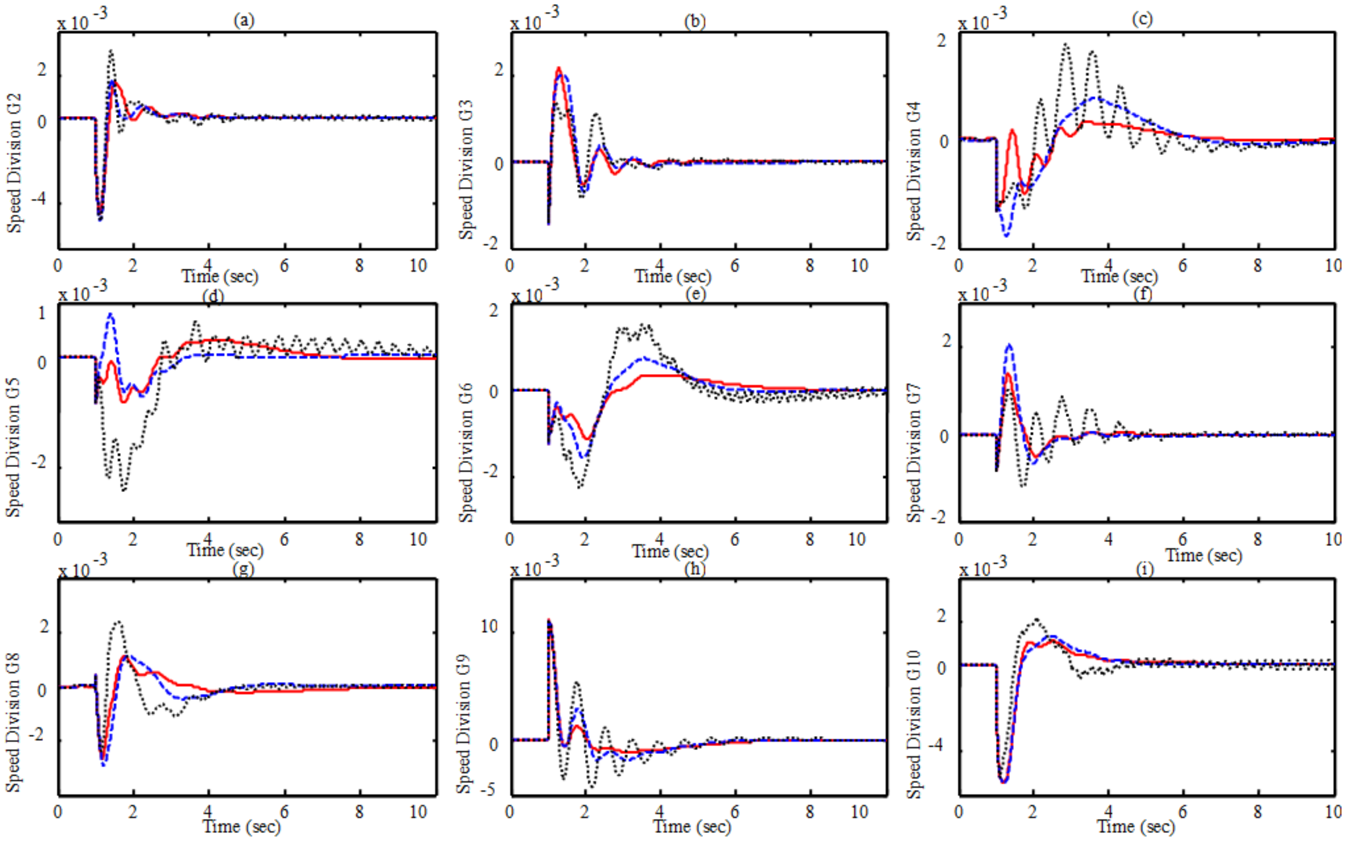

Figure 11. System response under scenario 1 with heavy loading condition, Solid (proposed-PSS), Dashed (PSO-PSS), Doted (C-PSS)

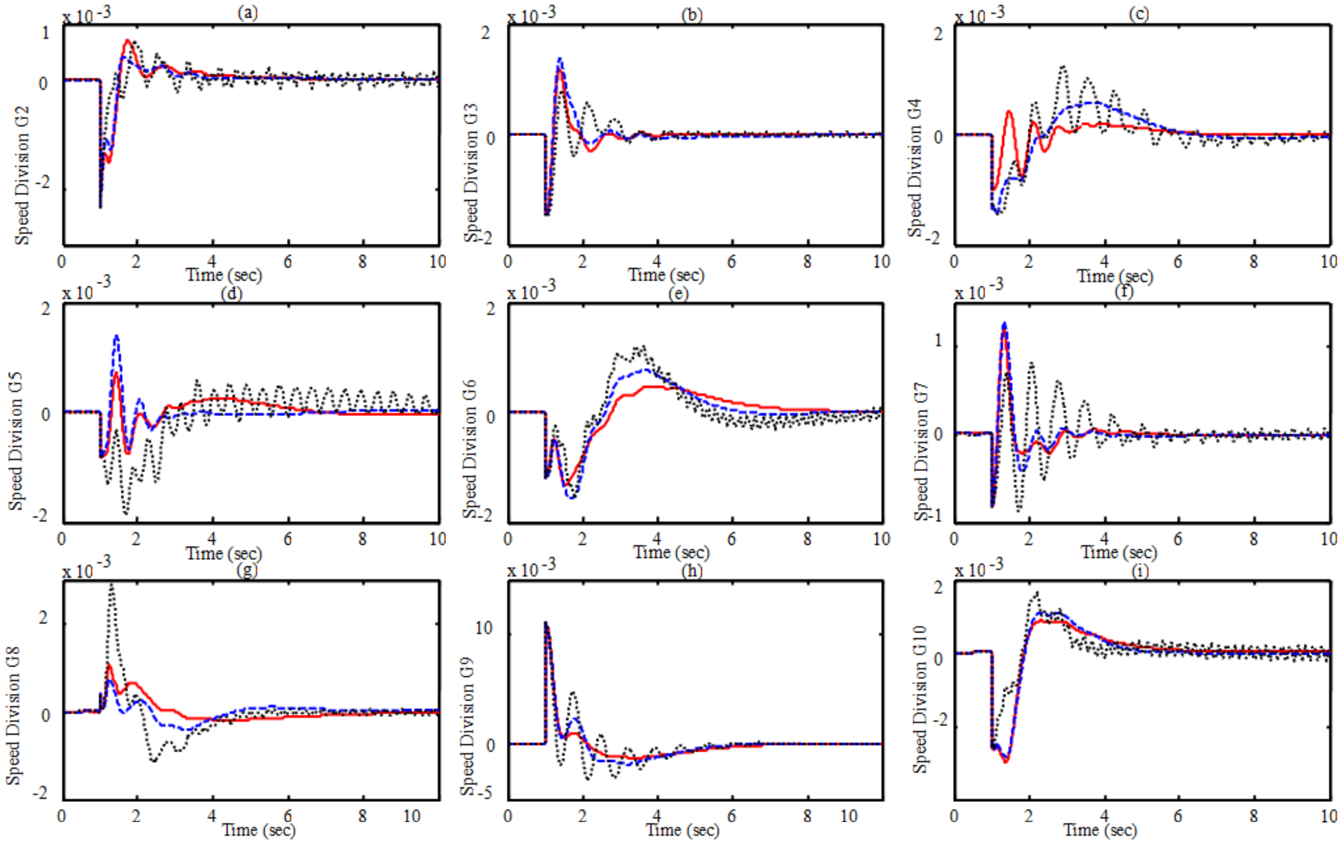

Figure 12. System response under scenario 2 with light loading condition, Solid (proposed-PSS), Dashed (PSO-PSS), Doted (C-PSS)

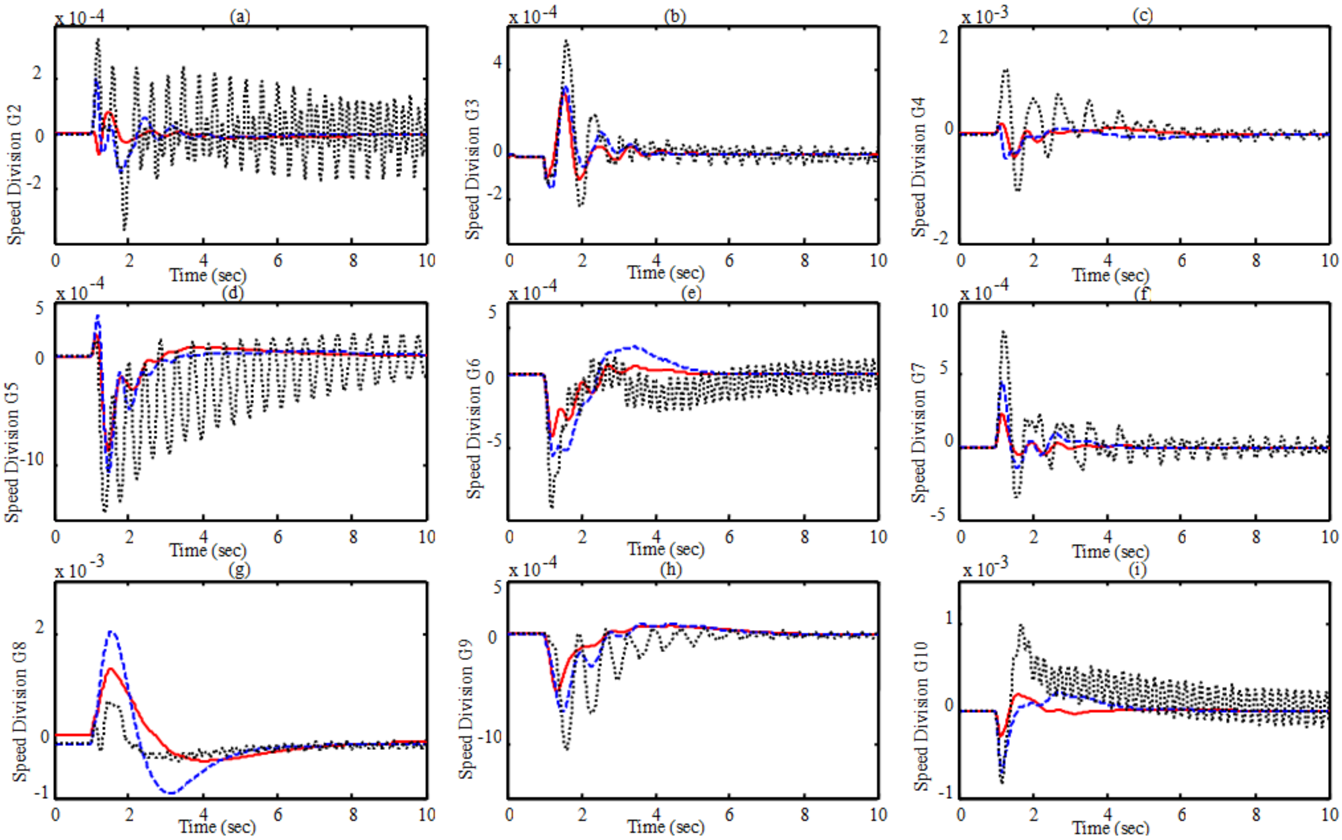

Figure 13. System response under scenario 3 with nominal loading condition, Solid (proposed-PSS), Dashed (PSO-PSS), Doted (C-PSS)

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