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# A NOVEL OF ARTIFICIAL BEE COLONY AND NEURAL NETWORK FOR MULTIMACHINE POWER SYSTEM STABILIZER DAMPING

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**Abstract**- An Artificial Neural Network (ANN) is proposed in this paper for multi machine Power System Stabilizer (PSS) damping. The proposed ANN is optimized with Artificial Bee Colony (ABC) to better learn as a controller in power system. Actually, the weights and bias of the ANN are important to improve its application. So, finding the weights and bias of ANN is proposed as an optimization problem to damp low frequency oscillation. This newly developed control strategy composed the advantages of ANN and ABC, which leads to a flexible controller with simple structure. The New England power system with 10 machine and 39-bus are proposed as a case study in comparison with Tabu Search (TS) through *FD* and *ITAE* performance indices under different operating condition. The proposed method guarantees a robust acceptable performance over a wide range of operating and system condition.

**Keywords:** Artificial Bee Colony (ABC), Artificial Neural Network (ANN), Multimachine Power System.

## I. INTRODUCTION

Power systems are used to convert natural energy into electric power. To optimize the performance of electrical equipment, ensure the quality of the electric power is important. In addition, the three-phase Alternating Current (AC) is generally used to transport the electricity. Actually, during the transportation, the active power balance and the reactive power balance must be maintained between generating and utilizing the AC power. Accordingly, those two balances correspond to two equilibrium points, frequency, and voltage.

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 power system operators [1]. 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 [3]. To overcome these problems of PSS design, intelligent optimization based techniques have been introduced [4].

Ant Colony (AC) is a powerful optimization technique, which is based on the behavior of the artificial ants, is inspired from real ants [5]. This algorithm works concurrently and independently and collective interaction via indirect communication leads to good solutions. The greedy heuristic helps find acceptable solution in the early solution in the early stages of the search process [6]. However, this algorithm has some disadvantage points as slower convergence than other heuristics and no centralized processor to guide AS towards good solutions. Accordingly, to tackle the mentioned problems the hybrid technique of Artificial Neural Network (ANN) with Artificial Bee Colony (ABC) is proposed to damp the low frequency oscillation in power system.

In this paper the weights and bias parameters of ANN is optimized with ABC, which leads to increasing the efficiency of controller in different load conditions. This strategy is tested over 10 machine 39-bus New England power system under various system configurations and loading conditions. This technique is compared with Tabu Search (TS) technique, which the simulation results show the superiority of the proposed technique. In this paper the section II shows the power system description. In section III and IV the proposed ANN and ABC are presented, respectively. Section V presents the simulation results, which compared with other technique. Conclusion is presented in section VI.

## II. POWER SYSTEM DESCRIPTION

The third-order model comprising of the electromechanical swing equation and the generator internal voltage equation [7] represents the generator. Figure 1, shows the main model of power system with location of controller [3-14]. The swing equations of this system are:

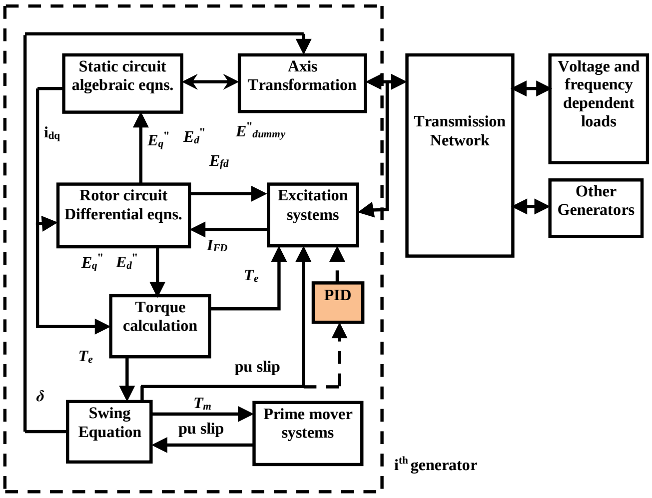


Figure 1. Structure of controller in power system [3]

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

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

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

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

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

## III. MULTI-LAYERED PERCEPTRON NEURAL NETWORK

The multi-layered feed-forward Neural Network (NN), which is known as the Multi-Layered Perceptron (MLP) NN, was developed in early 1970s, and is the most popular topology. This NN consists of an input layer, an output layer, and one or more hidden layers. The numbers of neuron in both input and output layers depend on the applied problem, while the numbers of neuron in the hidden layers are arbitrary and are usually decided by trial and error [8]. The MLP neural network with one hidden layer is presented in Figure 2. The layers in MLP neural networks are interconnected by communication links that are associated with weights that dictate the effect on the information passing through them [9].

A proposed ABC algorithm determines the weights. One of the popular training algorithms for the MLP NN is the error back-propagation algorithm [10], which is based on the gradient descent technique for error reduction. However, the conventional back-propagation method is too slow for many applications. In this paper, the ABC algorithm is proposed to optimize the weights of ANN. This algorithm is a meta-heuristic optimization technique, which adapts weight based on local gradient information. The size of weight update is determined by a separate update value. ABC algorithm is presented in section IV.

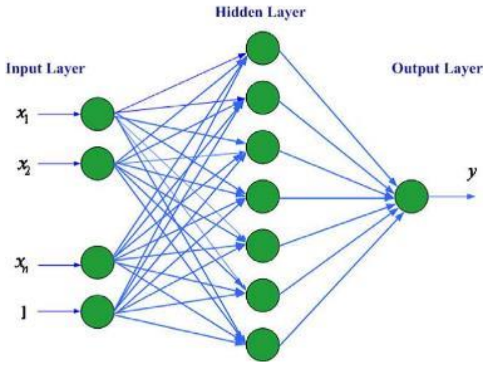


Figure 2. A typical Multi-Layered Perceptron (MLP) neural network with one hidden layer

## IV. ARTIFICIAL BEE COLONY

Recently, Karaboga and Basturk [11] have described an Artificial Bee Colony (ABC) algorithm based on the foraging behavior of the honeybees for numerical optimization problems. The algorithm simulates the intelligent foraging behavior of the honeybee swarms. It is a very simple, robust and population based stochastic optimization algorithm [12]. In the ABC algorithm, the colony of artificial bees contains three groups of bees, employed bees, onlookers, and scouts.

A bee waiting on the dance area for making decision to choose a food source is called an onlooker and a bee going to the food source visited by itself previously is named an employed bee. A bee carrying out random search is called a scout. In the ABC algorithm, first half of the colony consists of employed artificial bees and the second half constitutes the onlookers.

The employed bee whose food source is exhausted by the employed and onlooker bees becomes a scout. The main steps of the algorithm are given below [11, 12]:

- Initialize
- Repeat
- Place the employed bees on the food sources in memory
- Place the onlooker bees on the food sources in memory
- Send the scouts to the search area for discovering new food sources
- UNTIL (requirements are met)

In the ABC algorithm, each cycle of the search consists of three steps as, sending the employed bees onto the food sources, then measuring their nectar amounts. Selecting of the food sources by onlookers after sharing the information of employed bees and determining the nectar amount of the foods, determining the scout bees and then sending them onto possible food sources is final step. The flowchart of the proposed ABC algorithm is shown in Figure 3 [14]. In the ABC algorithm, the position of a food source represents a possible solution of the optimization problem and nectar amount of a food source corresponds to the quality (fitness) of the associated solution.

The number of the employed bees or the onlooker bees is equal to the number of solutions in the population. At the first step, the ABC generates a randomly distributed initial population $P$ ($G$ = 0) of SN solutions (food source positions), where SN denotes the size of population. Each solution (food source) $x_i$ ($i$ = 1, 2, ..., $S_N$) is a $D$-dimensional vector. Here, $D$ is the number of optimization parameters. After initialization, population of positions (solutions) is subjected to repeated cycles, $C$ = 1, 2, ..., $C_{\max}$, of search processes of employed bees, onlooker bees and scout bees.

An artificial employed or onlooker bee probabilistically produces a modification on the position (solution) in her memory for finding a new food source and tests the nectar amount (fitness value) of the new source (new solution). The artificial bees randomly select a food source position and produce a modification on the one existing in their memory. Provided that the nectar amount of the new source is higher than that of the previous one the bee memorizes the new position and forgets the old one. Otherwise, she keeps position of previous one. After all employed bees complete the search process, they share nectar information of food sources (solutions) and their position information with onlooker bees on dance area.

An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. As in the case of the employed bee, she produces a modification on the position (solution) in her memory and checks the nectar amount of the candidate source (solution). Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the old one [13]. An onlooker bee chooses a food source depending on the probability value associated with that food source, $p_i$, calculated by the following expression:

$$p_i = \frac{fit_i}{\sum_{n=1}^{S_N} fit_n} \tag{6}$$

where, $fit_i$ is the fitness value of the solution $i$ evaluated by its employed bee, which is proportional to the nectar amount of the food source in the position, $i$ and $S_N$ is the number of food sources which is equal to the number of employed bees ($B_N$). In this way, the employed bees exchange their information with the onlookers [14]. In order to produce a candidate food position from the old one, the ABC uses the following expression:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{7}$$

where, $k \in \{1, 2, ..., B_N\}$ and $j \in \{1, 2, ..., D\}$ are randomly chosen indexes. Although $k$ is determined randomly, it has to be different from $i$. $\varphi_{ij}$ is a random number between [-1, 1]. It controls the production of a neighbor food source position around $x_{ij}$ and the modification represents the comparison of neighbor food positions visually by the bee.

Above equation shows that as the difference between the parameters of the $x_{ij}$ and $x_{kj}$ decreases, the perturbation on the position $x_{ij}$ decreases, too. Thus, as the search approaches to the optimum solution in the search space, the step length is adaptively reduced [14]. If a parameter produced by this operation exceeds its predetermined limit, the parameter can be set to an acceptable value. In this work, the value of the parameter exceeding its limit is set to its limit value. The food source whose nectar is abandoned by bees is replaced with a new food source by scouts. In ABC algorithm, this is simulated by randomly producing a position and replacing it with abandoned one.

If a position cannot be improved further through a predetermined number of cycles called limit then that food source is assumed to be abandoned. After each candidate source position $v_{ij}$ is produced and then evaluated by the artificial bee, its performance is compared with that of $x_{ij}$. If the new food has equal or better nectar than the old source, it is replaced with the old one in the memory. Otherwise, the old one is retained. In other words, a greedy selection mechanism is employed as selection operation between old and current food sources. ABC algorithm in fact employs four different selection processes:

a. A global selection process used by the artificial onlooker bees for discovering promising regions

b. A local selection process carried out in a region by the artificial employed bees and the onlookers depending on local information (in case of real bees. This information includes the color, shape and fragrance of flowers), (bees will not be able to identify type of nectar source until they arrive at right location and discriminate among sources growing there based on their scent) for determining a neighbor food source around source in memory

c. A local selection process called greedy selection process carried out by all bees in that if the nectar amount of the candidate source is better than that of the present one, bee forgets present one and memorizes the candidate source. Otherwise, bee keeps present one in memory

d. A random selection process carried out by scouts

It is clear from the above explanation that there are three control parameters used in the basic ABC, the number of the food sources which is equal to the number of employed or onlooker bees ($S_N$), the value of limit and the Maximum Cycle Number (MCN) [14-15].

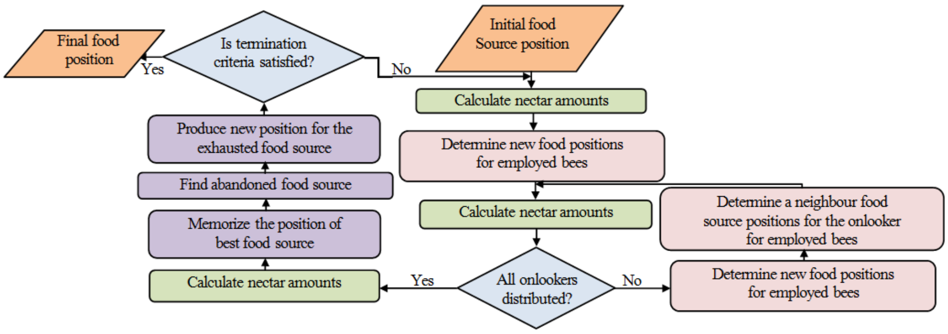


Figure 3. The flowchart of the proposed ABC algorithm [14]

## V. SIMULATION RESULTS

In this paper, the 10-machine 39-bus power system shown in Figure 4 is considered as a test case. To assess the effectiveness and robustness of the proposed method, wide range of loading conditions as nominal, light and heavy loading are considered. Details of the system data and operating condition are given in [3-16].

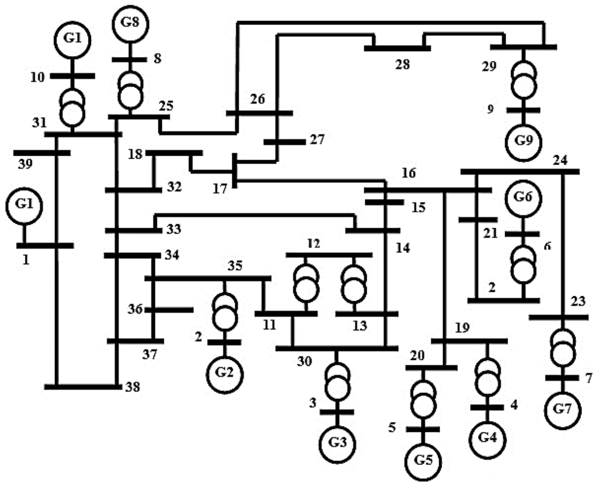

Figure 4. Ten-machine 39-bus New England power system [3]

### A. Nonlinear Time-Domain Simulation

To demonstrate the effectiveness and robustness of the proposed ANN based ABC controller, simulation studies are carried out under fault disturbances for three scenarios. For different operating conditions, performance of the proposed controller is compared to the PSSs, which tuned using the Tabu Search (TS) method in [16].

### A.1. 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. Permanent tripping of the faulted line clears the fault. Speed deviations of the generators in G5, G7, and G9 under nominal, heavy, and light load conditions are shown in Figure 5 respectively. It can be seen that the overshoot, undershoot, settling time and speed deviations of all machines are greatly reduced by applying the proposed technique.

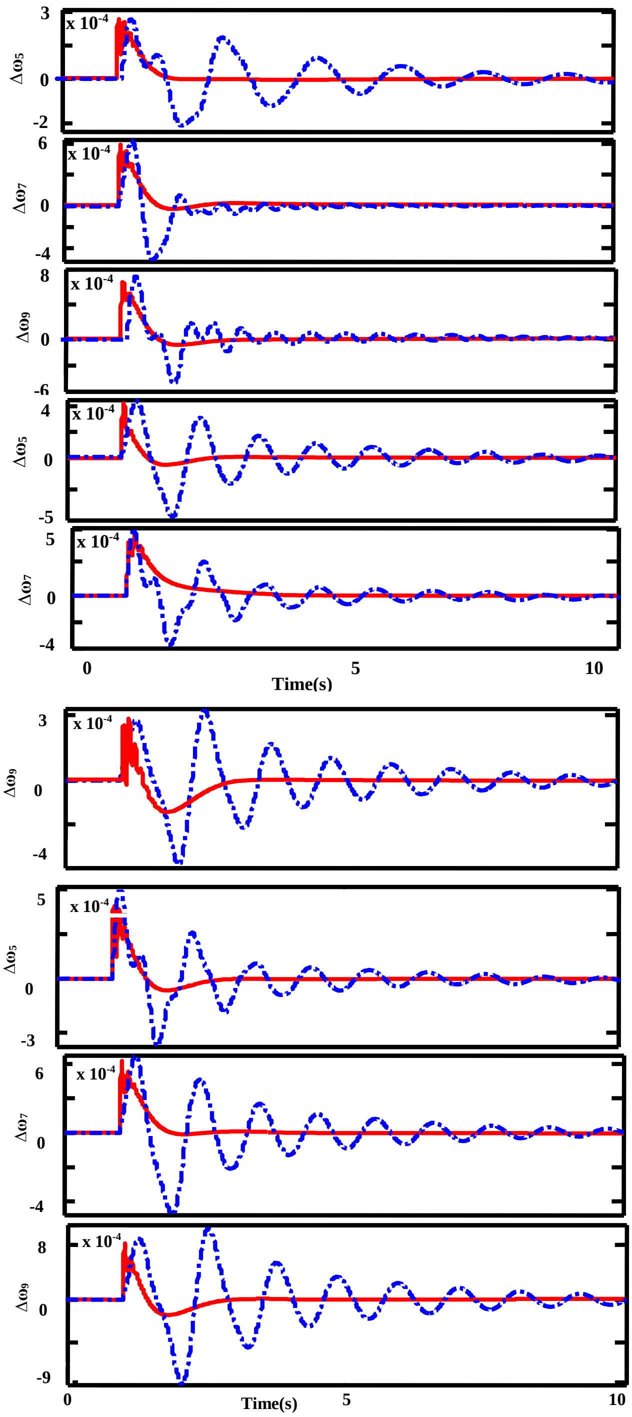


Figure 5. System response under scenario 1 with nominal, light and heavy loading conditions, solid (ANN-ABC), doted (TSPSS)

### A.2. Scenario 2

It is very important to test the controller under loading power factor operating condition. A 0.2 pu step increase in mechanical torque was applied at $t$ = 1.0, Figure 6 shows the result of simulation that are tested in different load conditions as nominal, heave and light, respectively.

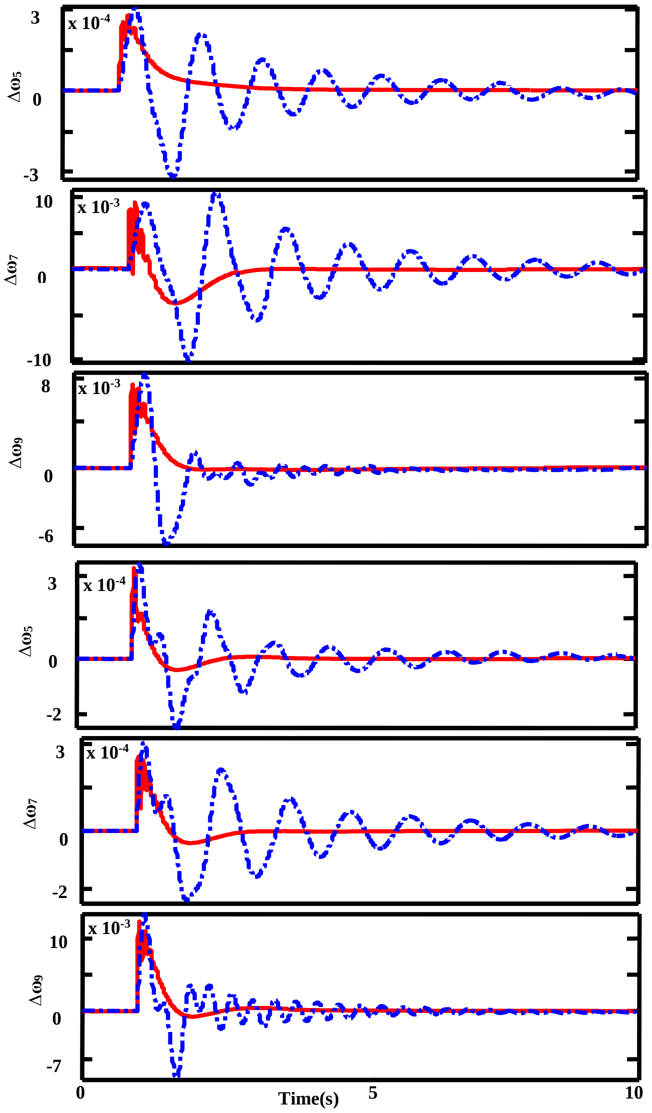

Figure 6. System response under scenario 2 with nominal, heave and light loading condition, solid (ANN-ABC), doted (TSPSS)

### A.3. Scenario 3

In this scenario a 0.2 pu step increase in mechanical torque was applied at $t$ = 0.5 sec and after a few seconds a 6-cycle three-phase fault at $t$ = 5 sec, on bus 26 at the end of line 26-29 for system will be applied. The results of simulation are shown in Figure 7 as nominal, heave and light, respectively.

To demonstrate robustness of the proposed method, two performance indices, *ITAE* and *FD* based on system performance characteristics are defined as [17, 18]:

$$ITAE_i = 100\int_0^{10} t(|\Delta\omega_i|)dt \qquad (8)$$

$$FD = (OS\times10^{-4})^2 + (US\times10^{-4})^2 + T_s{}^2 \qquad (9)$$

where, overshoot (*OS*), undershoot (*US*) and settling time (*T*) of rotor angle deviation of one machine is considered for evaluation of the *FD*. It is worth mentioning that the lower the values of these indices are, the better the system response in terms of time-domain characteristics is. Numerical results of performance robustness for all cases are listed in Tables 1 to 2. It can be seen that the values of these system performance characteristics with the proposed controller are much smaller.

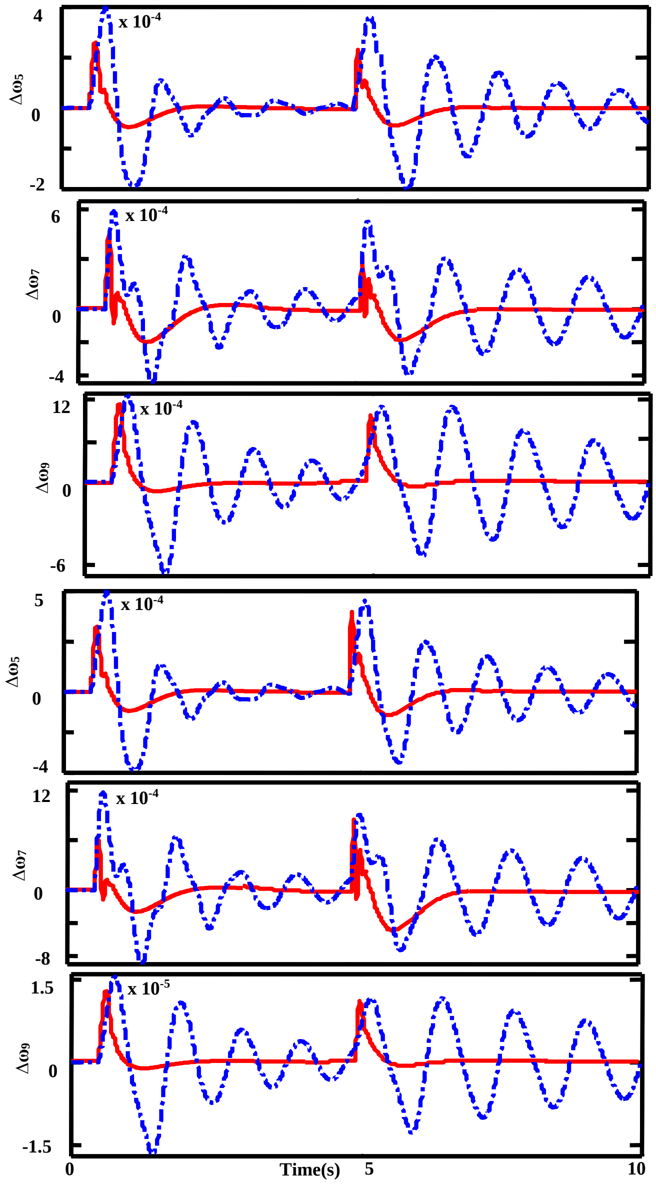

Figure 7. System response under scenario 3 with nominal, heavy and light loading condition, solid (ANN-ABC), doted (TSPSS)

## VI. CONCLUSIONS

In this paper an Artificial Neural Network (ANN) is proposed with Artificial Bee Colony (ABC) technique to solve the low frequency oscillation problem. Actually, the weights and bias of the ANN are important to improve its application. So, finding these parameters is proposed as an optimization problem to damp low frequency oscillation. This newly developed control strategy composed the advantages of ANN and ABC, which leads to a flexible controller with simple structure.

In this paper the New England power system with 10 machine and 39-bus are proposed as a case study in comparison with Tabu Search (TS) through *FD* and *ITAE* performance indices under different operating conditions. The proposed method guarantees a robust acceptable performance over a wide range of operating and system condition.

Table 1. Value of *ITAE* in different techniques

| Method | Scenario 1 | | | Scenario 2 | | | Scenario 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Nominal | Light | Heavy | Nominal | Light | Heavy | Nominal | Light | Heavy |
| TSPSS | 103.2 | 95.6 | 114.3 | 112.1 | 104.7 | 131.9 | 228.0 | 207.4 | 257.6 |
| ANN-ABC | 19.13 | 19.33 | 20.1 | 21.12 | 25.88 | 26.34 | 30.77 | 32.42 | 30.33 |

Table 2. Value of *FD* in different techniques

| Method | Scenario 1 | | | Scenario 2 | | | Scenario 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Nominal | Light | Heavy | Nominal | Light | Heavy | Nominal | Light | Heavy |
| TSPSS | 627 | 618 | 716 | 713 | 703 | 748 | 759 | 735 | 776 |
| ANN-ABC | 213 | 221 | 223 | 210 | 212 | 225 | 270 | 270 | 321 |

## NOMENCLATURES

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

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