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COORDINATED CONTROL OF LOW FREQUENCY OSCILLATIONS USING IMPROVED MONKEY ALGORITHM

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Abstract- This paper proposes an improved version of Monkey Algorithm (IMA) to simultaneous coordinated tuning of two power system stabilizers (PSSs) in a power system. A conventional lead-lag structure is considered for the controllers where the parameters of two PSSs are determined simultaneously by IMA. The numerical results are presented on a two-area 4-machine system to illustrate the feasibility of the IMA. To show the effectiveness of the designed controllers, a three phase fault is applied at a bus. The simulation study shows that the designed controller by IMA performs well in damping of oscillations.

Keywords: Monkey Algorithm, Low Frequency Oscillations, Power System Stabilizer, Dynamic Stability.

I. INTRODUCTION

It is well known that the power system stabilizers (PSSs) improves the stability of power systems through damping of low frequency modes [1-2] where several approaches such as pole-placement, optimal control, adaptive control, variable structure control [3-8] is used to PSS design problem.

Since, power system utilities prefer the conventional lead-lag power system stabilizer structure; heuristic algorithms are applied as efficient tools for optimal design of PSS to find the parameters of lead-lag controller. The authors in [9] presented an implementation using an evolutionary programming to look for the PSSs parameter. Genetic algorithm was used to optimal design of PSSs in [10]. In [11-12], simulated annealing and particle swarm optimization was used to design PSSs. In [13], neural network was used to design PSSs. Fuzzy theory and evolutionary algorithm was used to solve the problem in [14]. Different versions of IA are used in [15-18] to design controller to damp oscillations. Also the ability of the artificial bee colony and PSO algorithm were investigated in [19-20]. Also, different approaches are reported in [21-23] for designing PSSs to damp oscillations.

This paper uses MA as an alternative approach to design PSS. Since there are some difficulties with standard MA and cannot converge properly, in this paper a modification is proposed to overcome the difficulties associated with the standard MA. The improved version of MA (IMA) with an eigenvalue-based objective function is used to simultaneous coordinated design of two PSSs and the results obtained are compared with those obtained by the MA.

The paper is organized as follows: to make a proper background, the basic concept of the monkey algorithm is briefly explained in Section II followed by the descriptions of the proposed IMA. The optimization problem is formulated in Section III. The results obtained by IMA and MA in a study system are given in Section IV and some conclusions are drawn in Section V.

II. MONKEY ALGORITHM

This algorithm is inspired from the mountain-climbing processes of monkeys where the monkeys look for the highest mountain by climbing up from their positions. When each monkey gets to the top of the mountain, it looks around to find out whether there are higher mountains around or not. If yes, it will jump toward the mountain from the current position and then repeat the climbing until it reaches the top of the higher mountain. The MA is based on three main process namely as climb process, watch-jump process and somersault process. In the following the monkey algorithm and the proposed modified one are explained.

A. Standard Monkey Algorithm

In general, the MA works as follows [24]:

Step 1. Define the population size of monkeys (M), the climb number (N_c), the objective function and the decision variables. Input the system parameters and the boundaries of the decision variables. The optimization problem can be defined as:

minimize $f(x)$ subject to $x_{jL} \le x_j \le x_{jU}$, $(j = 1, 2, ..., n)$ where x_{jL} and x_{jU} are the lower and upper bounds for decision variables.

Step 2. Initialize a feasible position for each monkey, where the position of ith monkey is denoted as a vector with n dimension:

$$x_i = (x_{i1}, x_{i2}, ..., x_{in}) \quad , \quad i = 1, 2, ..., M \tag{1}$$

Step 3. Climb process. Climb process is a step by step procedure to change the monkeys' positions from the

initial positions to new ones that makes an improvement in the objective function. The climb process is as follows:
3-1. A vector is generated randomly as:

$$\Delta x_i = (\Delta x_{i1}, \Delta x_{i2}, ..., \Delta x_{in}) \quad , \quad i = 1, 2, ..., M \qquad (2)$$

where

$$\Delta x_{ij} = \begin{cases} +a & p(+a) = 0.5 \\ -a & p(-a) = 0.5 \end{cases} \qquad (3)$$

in which a is called the step length of the climb process.
3.2. Calculate the pseudo- gradient of the objective function f at point x_i.

$$f'_{ij} = \frac{f(x_i + \Delta x_i) - f(x_i - \Delta x_i)}{2\Delta x_{ij}} \quad , \; j = 1, 2, ..., n \qquad (4)$$

$$f'_{ij} = (f'_{i1}(x_i), f'_{i2}(x_i), ..., f'_{in}(x_i)) \qquad (5)$$

3.3. Define parameter $y = (y_1, y_2, ..., y_n)$ which is calculated as follows:

$$y_i = x_{ij} + a.\text{sign}(f'_{ij}(x_i)) \quad , \quad j = 1, 2, ..., n \qquad (6)$$

If $y = (y_1, y_2, ..., y_n)$ is feasible, then x_i is replaced by y, otherwise x_i remains unchanged. The steps 3-1 to 3-3 are repeated until there is no considerable changes on the values of objective function or the climb number N_c is reached.
Step 4. Watch-Jump process: After the climb process, each monkey arrives at its own mountaintop, therefore; each monkey will look around to find a higher mountain. If a higher mountain is found, the monkey will jump there. For this a parameter b is defined as eyesight of the monkey which is the maximal distance that the monkey can watch. The monkey jumps based on the following steps:
4-1. A real number y is generated randomly in the range of :

$$y \in (x_{ij} - b, x_{ij} + b) \quad , \quad j = 1, 2, ..., n \qquad (7)$$

4-2. If y is feasible and $f(y)$ is better than $f(x)$ for ith monkey ($f(y) > f(x)$), the position is updated; otherwise, step 4-1 is repeated.
Step 5. The climb process is repeated by considering y as initial position.
Step 6. Somersault process: In this step, the monkeys find out new searching domains. Taking the center of all the monkeys' positions as a pivot, each monkey will somersault to a new position forward or backward in the direction of pointing at the pivot. Based on the new position, the monkeys will keep on climbing. The somersault process is as follows:
6-1. First a somersault interval $[c, d]$ is defined which the maximum distance that monkeys can somersault is. A real number α is generated randomly within the somersault interval.
6-2. Defines parameter y as follows:

$$y_j = x_{ij} + \alpha(p_j - x_{ij}) \qquad (8)$$

$$p_j = \frac{1}{M} \sum_{i=1}^{M} x_{ij} \quad , \quad j = 1, 2, ..., n \qquad (9)$$

where p is somersault pivot.
6-3. If $y = (y_1, y_2, ..., y_n)$ is feasible then x will be replaced by y, otherwise, repeat 6-1, 6-3 until a feasible y is found.
Step 7. Repeat steps 3-6 until the stopping criterion (maximum number of iteration) is met.
By the above description, the principle of MA can be summarized in Figure 1.

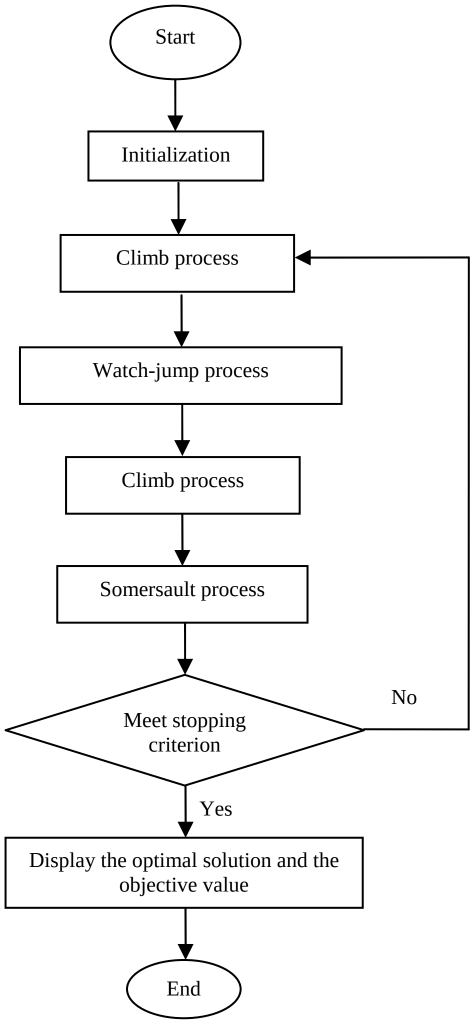

Figure 1. General principle of the MA

III. THE PROPOSED IMPROVED MONKEY ALGORITHM (IMA)

In the population based heuristic algorithms, two common aspects should be taken into account: exploration and exploitation. The exploration is the ability to investigate the search space for finding new and better solutions, where the exploitation is the ability of finding the optima around a good solution. To have a high performance search, an essential key is having a suitable trade-off between exploration and exploitation. MA may fall into a local optimum early in a run on some optimization problems. In other words, the algorithm approaches the neighborhood of the global optimum but for some reasons it fails to converge to the global optimum. The stagnation could be due to the following reason:

In the standard MA, there is no a sufficient learning mechanism in the algorithm. In other words, the monkeys don't learn from each other and the information obtained by each monkey doesn't transfer to other monkeys. This leads the algorithm to be trapped easily in the local optimum.

Furthermore, improvement of the position of the monkeys in the range of (x_{ij}-b, x_{ij}+b) is done randomly that makes the algorithm have a long running time to find a good solution. To overcome the above problems, a suggestion is given in which the climb process and somersault process remain unchanged but watch-jump process is changed a follows:

Since in watch-jump process, each monkey will look around to find a higher mountain and if a higher mountain is found, the monkey will jump there which is based on a random process (step 4) without considering the position of other monkeys. In this paper, instead of making a decision based on local information by each monkey by a random process, the information of each monkeys are transferred and a decision for changing the position is made based on the obtained information by other monkeys as below:

$$y_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \quad , \quad i = 1,2,...,M \qquad j \in \{1,2,...,n\} \qquad k \in \{1,2,...,M\}, k \neq i \tag{10}$$

where, φ_{ij} is a random number in the range of [-1,1], j and k are chosen randomly in range of $\{1,2,...,n\}$ and $\{1,2,...,M\}$, respectively in which $k \neq i$. If the new position is better than the previous one, the monkey will jump there, otherwise, the position remains unchanged but the monkey tries to improve its position by repeating this step. For this, a counter (N_w) is defined and this step is repeated until the number of counter (N_w) is reached. y_{ij} must be feasible otherwise, y_{ij} is selected as :

$$\text{if} \quad y_{ij} > x_{ij}^{\max} \Rightarrow y_{ij} = x_{ij}^{\max} \tag{11}$$

$$\text{if} \quad y_{ij} < x_{ij}^{\min} \Rightarrow y_{ij} = x_{ij}^{\min} \tag{12}$$

IV. STUDY SYSTEM AND PROBLEM FORMULATION

This test system is a two-area-4-machine system which is shown in Figure 2. The subtransient model for the generators, and the IEEE-type DC1 and DC2 excitation systems are used for machines 1 and 4, respectively. The IEEE-type ST3 compound source rectifier exciter model is used for machine 2, and the first-order simplified model for the excitation systems is used for machine 2.

Two PSSs are going to be designed for the above system and placed on machines 2 and 3. The structure shown by Figure 3 is used for each PSS where the input (u) to PSS could be generator speed (GS) or the generator electrical torque (GET). In this paper, the generator speed (GS) is considered as input.

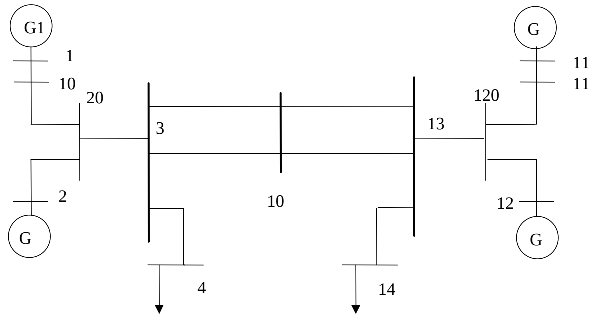

Figure 2. Single-line diagram of a two-area study system

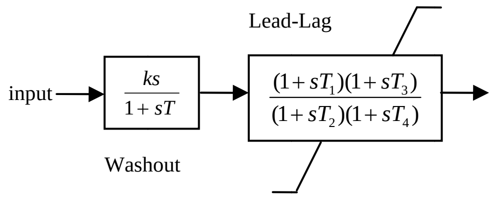

Figure 3. Conventional lead-lag supplemental controller block diagram for PSS

The parameters of the PSSs, K, T, T_1, T_2, T_3, T_4, are determined by IMA and MA by optimizing the following objective or cost function:

$$f = \max(\text{real}(s) - \min(-\beta \times \text{abs}(\frac{\text{imag}(s)}{\text{real}(s)}), \alpha)) \tag{13}$$

where in this study β is set to be 0.1. Also, a value α= - 0.2 is considered adequate for an acceptable settling time. This fitness function will place the system closed-loop eigenvalues in the D-shape sector shown in Figure 4.

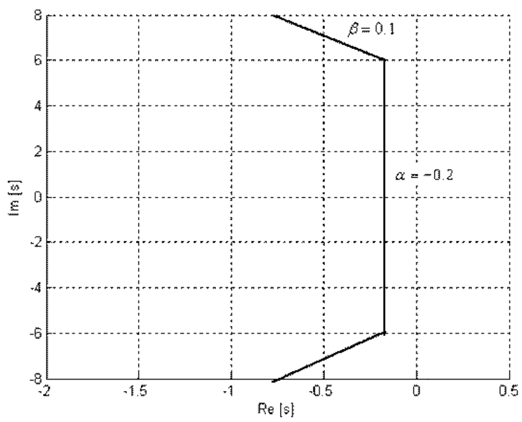

Figure 4. A D-shape sector in the s-plane

Furthermore, the design problem can be formulated as the following constrained optimization problem, where the constraints are the supplementary controller parameter bounds:

$$0 \le k \le 50, \; 0 \le T \le 5, \; 0 \le T_1 \le 2 \qquad 0 \le T_2 \le 2, \; 0 \le T_3 \le 2, \; 0 \le T_4 \le 2 \tag{14}$$

The IMA and MA are applied to solve this optimization problem and search for optimal or near optimal set of the PSSs parameters.

V. DESIGNING OF SUPPLEMENTARY CONTROLLERS USING IMA AND MA

To provide a reasonable damping for the system, the PSSs are designed using IMA and MA. For this, the parameters of the controllers; K, T, T_1, T_2, T_3, T_4 (for the first PSS) and K, T, T_1, T_2, T_3, T_4 (for the second PSS) are determined simultaneously by IMA and MA. The first step to implement the IMA and MA is generating the initial population (M monkeys) where M is considered to be 5. The step length of the climb process (a) and the climb number (N_c) are set to be 0.1 and 10, respectively. Also, N_w is set to be 200 in IMA.

Each population is a solution to the problem which determines the parameters of the PSSs; i.e.; K, T, T_1, T_2, T_3, T_4; K, T, T_1, T_2, T_3, T_4. During each generation, the monkeys are evaluated with some measure of fitness, which is calculated from the objective function defined in (13) subject to (14). Then the best monkey is chosen. In the current problem, the best monkey is the one that has minimum fitness. The algorithm is implemented based on Figure 1 and continue until the last iteration is met. In this paper, the number of iteration is set to be 20. To find the best value for the controller, K, T, T_1, T_2, T_3, T_4; the algorithms are run for 10 independent runs under different random seeds. The results obtained by two algorithms are shown in Table 1.

Table 1. The obtained parameters of PSSs for machines 2 and 3 by IMA and MA

Algorithm		K	T	T_1	T_2	T_3	T_4
MA	PSS1	26.02	2.742	1.166	0.445	1.203	0.159
	PSS2	35.65	2.704	1.173	0.647	0.923	0.546
IMA	PSS1	33.47	1.806	1.443	0.096	1.03	0.438
	PSS2	46.32	1.261	0.745	0.999	1.113	1.234

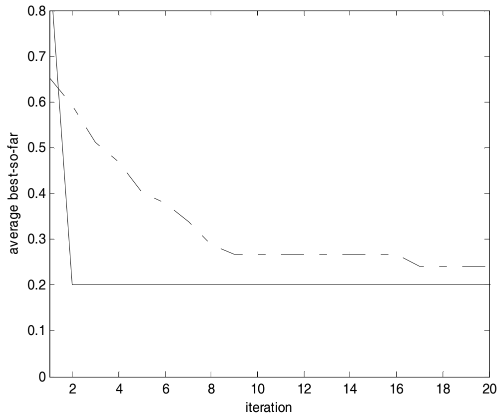

Figure 5. Convergence characteristics of IMA and MA on the average best-so-far in finding the parameters of PSSs

The convergence test is carried out to determine the quickness of the proposed algorithm. For two designed controllers by IMA and MA, the best-so-far of cost function of each run is recorded and averaged over 10 independent runs. To have a better clarity, the convergence characteristics in finding the best values of the supplementary controllers parameters is given in Figure 5 for two algorithms. This figure shows the superiority of IMA over the MA in finding the solution in early iterations.

The obtained supplementary controllers by IMA and MA are placed in the study system (Figure 3). To show the effectiveness of the designed controllers, a time-domain analysis is performed for the study system. A three-phase fault is applied in one of the tie circuits at bus 3. The fault persisted for 70.0 ms; following this, the faulted circuit was disconnected by appropriate circuit breaker. The system operated with one tie circuit connecting buses 3 and 101.The dynamic behavior of the system was evaluated for 15 s. The machine angles, δ, with respect to a particular machine, were computed over the simulation period and shown in Figures 6-7. As it is evident from the simulation results in the time domain, the damping is poor in the absence of any PSSs. By adding the controllers, the performance of the system is improved but the one designed by IMA performs better in damping of the oscillations.

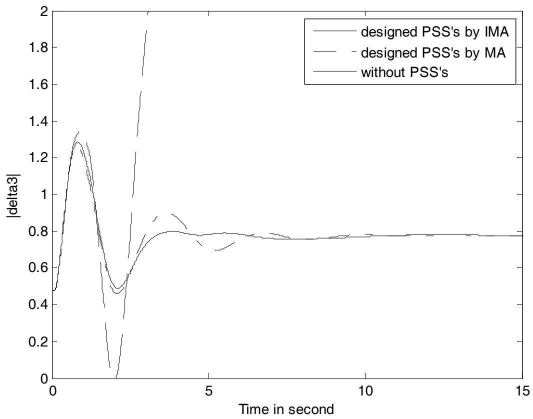

Figure 6. The response of generator 3 to a three-phase fault

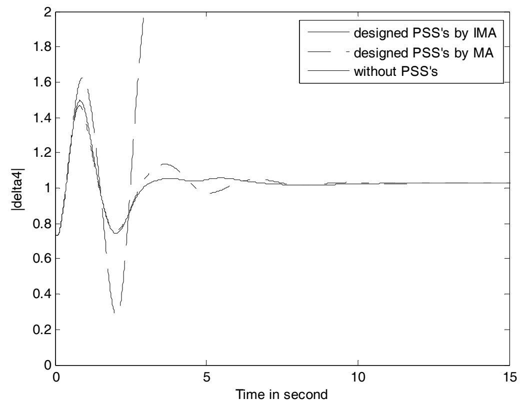

Figure 7. The response of generator 4 to a three-phase fault

VI. CONCLUSIONS

In this paper a modification is proposed to overcome the difficulties associated with the standard MA. The ability of an improved version of Monkey Algorithm (IMA) is investigated in designing two PSSs to damp the power system oscillations. For this the parameters of the controllers are determined by IMA and MA using an eigenvalue-based objective function. To show the effectiveness of designed controllers, a three-phase fault is applied at a bus. The simulation study shows that the IMA finds the solution in early iterations. Also, the designed controllers by IMA performs much better that the one designed by MA.

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