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Coordinated control of low-frequency oscillations using real immune algorithm with population management

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ABSTRACT

This paper proposes a modified version of real immune algorithm (RIA) using population management, namely, RIAPM, to simultaneous coordinated tuning of power system stabilizers (PSSs) in a power system. A conventional lead-lag structure is considered for the controllers. Since, the parameters of lead-lag controllers are continuous variables to be found and an infinite number of candidate solutions will exist, therefore a modification will be considered to RIA to reduce the search space gradually, in order to get a more detailed investigation in a smaller region. Using the RIAPM, the parameters of the damping controllers are optimized simultaneously and the interactions among the controllers are considered. The numerical results are presented on a 2-area 4-machine system to illustrate the feasibility of the proposed method. To show the effectiveness of the designed controllers, a three-phase fault is applied at a bus. The simulation study shows that the RIAPM performs better than RIA.

1. Introduction

To provide a secure operation for power plants and energy saving, damping of power system oscillations between interconnected areas has become one of the major problems in the power system stability area and have received a great deal of attention. It is known that PSS is an efficient tool for improving the dynamic stability of power systems by damping low frequency modes [1,2]. The frequency of these modes ranges from 0.2 Hz to 2.5 Hz consisting three main modes; local modes, inter-area modes and inter-plant modes. Since 1981, several approaches based on modern control theory have been applied to the PSS design problem including; optimal control, adaptive control, variable structure control [3–8]. Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead-lag power system stabilizer structure. The reason is that the modern control techniques may give a controller with a high order which is difficult to implement.

Recently, there has been a growing interest in algorithms inspired from the observation of natural phenomenon to seek the optimal design of PSS in a power system by the researches around the world. Evolutionary programming was used to optimal design of PSSs in [9]. The authors in [10] presented an implementation using a genetic algorithm (GA) to look for the PSSs parameter. In [11,12], the author proposed a solution procedure employing simulated annealing and particle swarm optimization to search for the solution. In [13], neural network was used to design PSSs. In [14], fuzzy theory and evolutionary algorithm were employed to solve the problem.

The authors in [15–17] used different versions of IA, including binary version of IA (BIA) and real version of IA (RIA) to design PSS or supplementary controller for SVC to damp oscillations. It was revealed that RIA performs better than BIA in designing the controllers.

In this paper, a modified version of RIA is applied by making use of the population management, namely as RIAPM where it differs from RIA by the use of local search and distance measures for population management. By the population management, the RIAPM can control the diversity of a small population of high-quality antibodies, thereby avoiding slow or premature convergence. RIAPM with an eigenvalue-based objective function is used to simultaneous coordinated design of two PSSs. Also, the RIA is applied and the results are compared with those obtained by the RIAPM. It should be noted that in the work presented in [16], a non-coordinated design was carried out.

The paper is organized as follows: to make a proper background, the basic concept of the immune algorithm is briefly explained in Section 2 followed by the descriptions of RIAPM in Section 3. The optimization problem is formulated in Section 4.

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The results of the RIA and RIAPM in a study system are given in Section 5 and some conclusions are drawn in Section 6.

2. Overview of immune algorithm

The IA has desirable characteristics as an optimization tool and offers significant advantages over traditional methods. In the IA, antigen represents the problem to be solved. An antibody set is generated where each member represents a candidate solution. Also, affinity is the fit of an antibody to the antigen. In the IA, the role of antibody lies in eliminating the antigen, while the lymphocyte helps to produce the antibody [18,19].

In the immune system, there are two kinds of lymphocyte; T and B; where each of them has its own function. The T lymphocytes develop in bone marrow and travel to thymus to mature. The B lymphocytes develop and mature within the bone marrow. The main purpose of the immune system is to recognize all cells within the body and categorize those cells as self or non-self. Self or self antigens are those cells that originally belong to the organism and are harmless to their functioning. The disease-causing elements are known as non-self.

Both B-cells and T-cells have receptors that are responsible for recognizing antigenic patterns by different function. The attraction between an antigen and a receptor cell (or degree of binding) is known as affinity. To handle the infection successfully and effectively, both B-cells and T-cells may be required. After successful recognition, cells capable of binding with non-self antigens are cloned.

In the IA the elements of the population undergo mutations resulting in a subpopulation of cells that are slightly different. Since the mutation rate is high, this mutation is called hypermutation.

By the above description, the principle of IA can be summarized in Fig. 1.

As Fig. 1 shows at the first step, n antibodies are generated randomly and evaluated using a suitable affinity measure. While the affinity of all antibodies are known, new population is generated through three steps; replacement, cloning and hypermutation. These three steps maintain the diversity and help the algorithm to expand the search space. In the replacement step, the low antibodies (in the case of minimizing) are replaced. Those with the highest affinity are selected to proliferate by cloning where the cloning rate of each immune cell is proportional to its affinity. If the high affinity antibody has not been cloned, hypermutation is applied where the mutation rate for each immune cell is inversely proportional to its affinity. When the new population is generated, IA continues with repeated evaluation of the antibodies through replacement, cloning and hypermutation until the termination criterion is met. The termination criterion could be the number of iterations or when an antibody of maximal affinity is found.

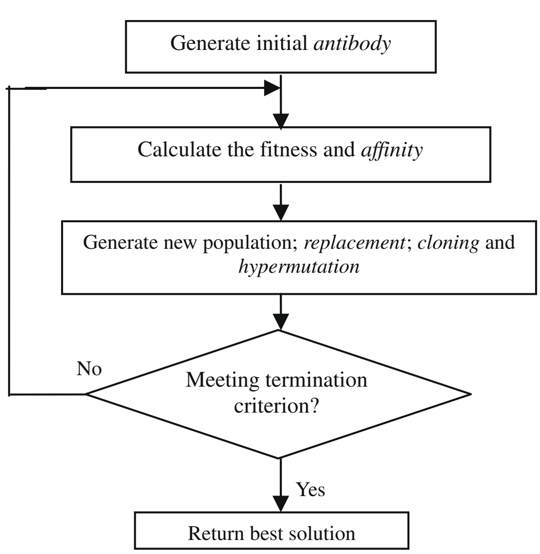

Fig. 1. General principle of the IA.

The IA can be implemented through the BIA and RIA. The RIA uses the real codes and the replacement; cloning and hypermutation are applied to the variable directly. The proposed RIA with population management (RIAPM) is explained below.

3. Proposed real immune algorithm with the population management (RIAPM)

Since, the parameters of lead-lag controllers are continuous variables to be found, therefore an infinite number of candidate solutions will exist. For this a modification will be considered to reduce the search space gradually, in order to get a more detailed investigation in a smaller region. The adaptation can be implemented pruning the search space after a certain number of unsuccessful generations. Also, a local search is added to RIA in which an immune search is used to explore the search space and a local search to exploit information in the search region. The local search used is a hill-climbing one. The proposed RIAPM can be explained as follows:

In RIA, the initial process can produce n antibodies randomly. Each antibody will be evaluated by a fitness function. Then, the first l antibodies with the best fitness function will be selected. Now the local search is applied on the selected l antibodies. This Local search is a hill-climbing one, where a neighborhood is considered for each selected l antibodies. The algorithm searches the neighborhood of the l selected antibodies to find a solution with more improvement in the value of fitness function. If such a solution exists, the old antibody is replaced with the newly obtained antibody. This local search can be repeated m times where m is a constant value defined by the user. Furthermore, the local search governs the exploration by adapting the search space as follows.

3.1. Evaluating the population

Throughout the process, all individuals that are successfully improved by the local search method are recorded, giving rise to a collection of enhanced solutions. This collection is void at the beginning, and gradually is filled; up to exceed the size of the initial population by storing the best solution in each iteration. The upper and lower values for each parameter in the collection are determined. From these values, new search limits (reducing of search space) are defined and explored in the next generations.

3.2. Population management

Since the reduction of search space may result in premature convergence, the population management can be added to the algorithm, which controls the diversity of a small population of high-quality solutions. This immune algorithm with population management (RIAPM) uses a distance measure d and a threshold that determines whether an antibody solution can be added to the population or not. By calculating the distance measure d and defining a threshold, the quality of the solution and the contribution that the solution makes to the diversity of the population will be taken into account. In other words, to evaluate whether a candidate solution sufficiently diversifies the population, a distance measure d is used that determines for each pair of solutions their