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Design of a Supplementary Controller for SVC Using Immune Algorithm

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Abstract: This paper investigates the ability of Immune Algorithm (IA) in designing a supplementary controller for Static Var Compensators (SVC) to damp the power system inter-area oscillation. For this the parameters of the supplementary controller are determined by IA using an eigenvalue-based objective function. The numerical results are presented on a 2-area 4-machine system to illustrate the feasibility of the proposed method. Also, to compare the results obtained by IA, a simple Genetic Algorithm (GA) is applied. Furthermore, to validate the designed controllers by IA and GA a supplementary controller is designed by H_∞ controller using loop shaping method. To show the effectiveness of the designed controllers, a three phase fault is applied at a bus. The simulation study shows that the designed controllers improve the stability of the system.

1. INTRODUCTION

Power system stability is a complex subject that has challenged power system engineers for many years. Poorly damped low-frequency (0.1–3 Hz) oscillations are inherent in inter-connected power systems. In the last three decades, the applications of Flexible AC Transmission Systems (FACTS) devices for damping inter-area oscillations have been suggested and proven to have additional benefits for increasing system damping, in addition to their primary functions, for instance, voltage control and power flow control. These devices are usually installed on transmission lines and, therefore, have direct access to the variables, which have the highest sensitivity to the inter-area oscillatory modes (Farsangi, *et al*., 2007).

Many modern control techniques have been adopted around the world to design a supplementary controller for SVC (Zhao and Jiang, 1995, 1998; Pourbeik and Gibbard, 1996; Oliveira, 1994; Zhou, 1993; Larsen and Swann 1981; Kundur, 1994). Despite the potential of modern control techniques with different structures, intelligent control is used to design a conventional lead-lag structure.

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown in many works that these algorithms are good replacement as tools to solve complex computational problems (Lee and El-Sharkawi, 2002, 2003; Lee, 2005). Various heuristic approaches have been used to solve different problems, including genetic algorithm, tabu search, simulated annealing, ant colony system and particle swarm optimization.

In view of this, in this paper an immune algorithm with an eigenvalue-based objective function is used to design supplementary controller for SVC to damp the oscillations.

The paper is organized as follows: to make a proper background, the basic concept of the IA and GA are briefly explained in Section 2. The optimization problem is formulated in Section 3. The results of the IA in a study system are given in Section 4 and some conclusions are drawn in Section 5.

2. OVERVIEW OF GA and IA

2.1 Immune Algorithm (Clonal Selection)

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 (Musilek, *et al*., 2006; Corn and Dorigo, 1999).

In the immune system, there are two kind 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 its 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.

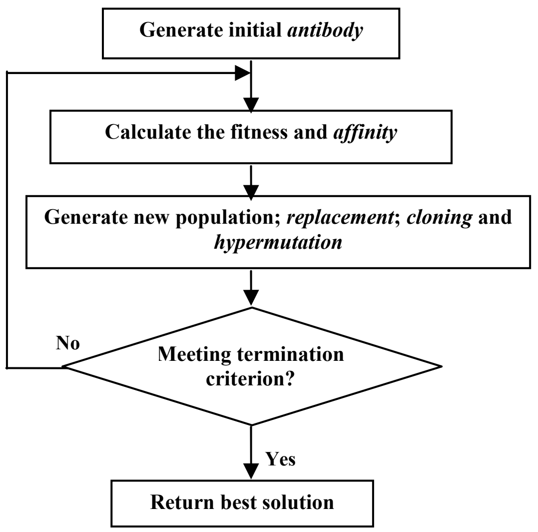

Fig. 1. General principle of the immune algorithm.

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 is 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 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 (Musilek, *et al.*, 2006). 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.

2.2 Genetic Algorithm

GA is a search algorithm based on the mechanism of genetic and natural selection. The GA starts with random generation of initial population and then the selection, crossover and mutation operations are preceded until the fitness function converges to a maximum or the maximal number of generations is reached. A typical simple genetic algorithm is described in detail by (Goldberg, 1998).

3. STUDY SYSTEM AND PROBLEM FORMULATION

A 2-area-4-machine system is used. This test system is illustrated in Fig. 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 3.

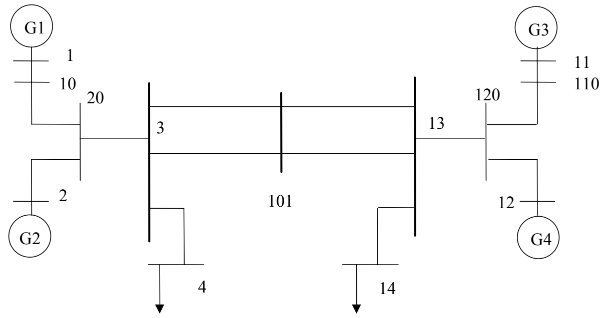

Fig. 2. Single-line diagram of a 2-area study system.

One SVC is located at bus 101, where voltage swings are the greatest without the SVC. A supplementary controller for SVC is going to be designed using IA. The following structure shown by Fig. 3 is used for the controller where the input to the controller could be the real power of line 13-120.

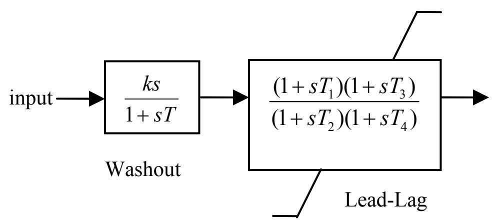

Fig. 3. A lead-lag structure model block diagram: supplementary controller for SVC.

A damping factor ς of around 10% to 20% for the troublesome low frequency electromemchanical mode is considered adequate. A damping factor of 10% would be acceptable to most utilities and can be adopted as the minimum requirement. Further, having the real part of rotor mode eigenvalue (s) restricted to be less than a value, say α, guarantees a minimum decay rate α. A value α = - 0.5 is considered adequate for an acceptable settling time. The closed-loop rotor mode location should simultaneously satisfy these two constraints for an acceptable small disturbance response of the controlled system.

Therefore, the parameters of the supplementary controller, T, T_1, T_2, T_3, T_4, are determined by IA and GA by optimizing the following objective or cost function:

$$f = \max(real(s) - \min(-\beta * abs(imag(s)), \alpha)) \qquad (1)$$

where in this study β is set to be 1. This fitness function will place the system closed-loop eigenvalues in the D-shape sector shown in Fig. 4.

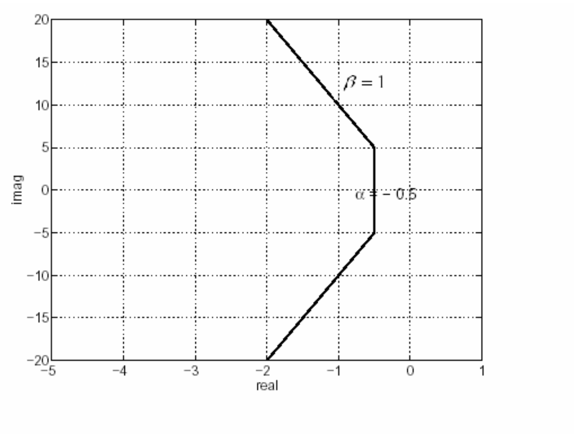

Fig. 4. A D-shape sector in the s-plane.

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

$$Minimize\ f\ subject\ to$$

$$\begin{cases} 0 \le T \le 50 \\ 0 \le T_1 \le 5 \\ 0.001 \le T_2 \le 5 \\ 0 \le T_3 \le 5 \\ 0.001 \le T_4 \le 5 \end{cases} \qquad (2)$$

IA and GA are applied to solve this optimization problem and search for optimal or near optimal set of supplementary controller for SVC.

4 . DESIGNING OF SUPPLEMENTARY CONTROLLER

A population of n antibodies are generated randomly, where n is considered to be 50. The goal of the optimization is to find the best value for the controller parameters, T, T_1, T_2, T_3, T_4 (Fig. 3). Therefore, a configuration is considered for each antibody as a vector $[T, T_1, T_2, T_3, T_4]$.
During each generation, the antibodies are evaluated with some measure of fitness, which is calculated from the objective function defined in equation (1) subject to (2). Then the best antibody is chosen. In the current problem, the best antibody is the one that has minimum fitness. This antibody is chosen as antigen and the affinity of other antibodies is calculated with the selected antigen. The affinity of each antibody is calculated by the following equation:

$$affinity = \frac{f(antigen)}{f(antibody)} \qquad (3)$$

Moving to a new generation is based on the antibodies with the high and low affinity by using cloning and replacement. Also, the mutation is applied to each generation in order to recognize not only the antigen itself but also antigens that are similar.

The above procedure continues until the last iteration is met. In this paper, the number of iteration is set to be 100. The following values for T, T_1, T_2, T_3, T_4 is found by IA as follows:

$$T = 48.534, T_1 = 2.17, T_2 = 4.653, T_3 = 1.117, T_4 = 4.956$$

To validate the obtained result by IA, a simple GA is applied. The number of chromosomes in the population is set to be 50, which is the same as in IA. One point crossover is applied with the crossover probability $p_c = 0.9$ and the mutation probability is selected to be $p_m = 0.01$. Also, the number of iterations is considered to be 100, which is the stopping criteria used in IA. The obtained parameters by GA are as follows:

$$T = 48.436, T_1 = 1.014, T_2 = 3.926, T_3 = 1.170, T_4 = 3.239$$

Owing to the randomness of the heuristic algorithms, their performance cannot be judged by the result of a single run. Thus, for the designed supplementary controllers for SVC, both algorithms are run for 10 independent runs under different random seeds and the best-so-far of each run are recorded and averaged over 10 independent runs. The 50% of the obtained results by IA reach to a minimum cost function (best solution) equal to 7.26 and 30% of the obtained results by GA reach a minimum cost function equal to 7.38.

To have a better clarity, the convergence characteristics in finding the best values of supplementary controllers are given in Fig. 5. This figure shows that IA is performing well in finding the solution.

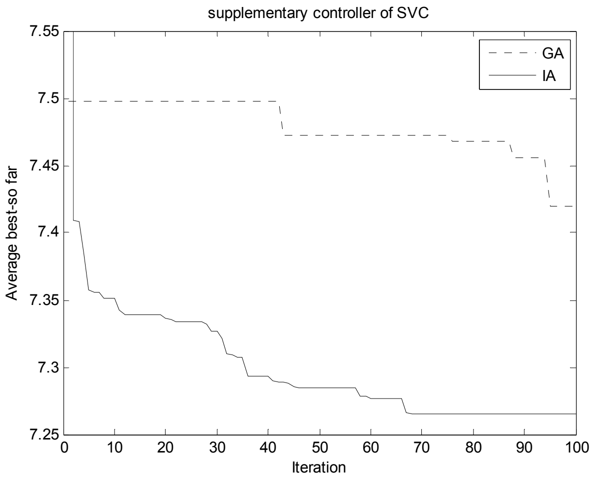

Fig. 5. Convergence characteristics of IA and GA on the average best-so-far function in finding the supplementary controller for SVC.

To validate the obtained results by IA and GA, a supplementary controller is designed by H_∞ controller using loop shaping method (Skogestad and Postethwaite, 1996). The following controller is found by loop shaping method:

$$k = \frac{s^3 + 14.8\,s^2 + 699.4\,s - 2422}{s^3 + 416.3\,s^2 + 2462\,s} \tag{4}$$

The obtained supplementary controllers for SVC by IA, GA and loop shaping method are placed in the study system (Fig. 2). To show the effectiveness of the designed supplementary controller for SVC, a time-domain analysis is performed for the study system. A three-phase fault is applied in one of the tie circuits at bus 101. 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 voltage magnitude at fault bus and the machine angles, δ, with respect to a particular machine, were computed over the simulation period and shown in Figs. 6-8.

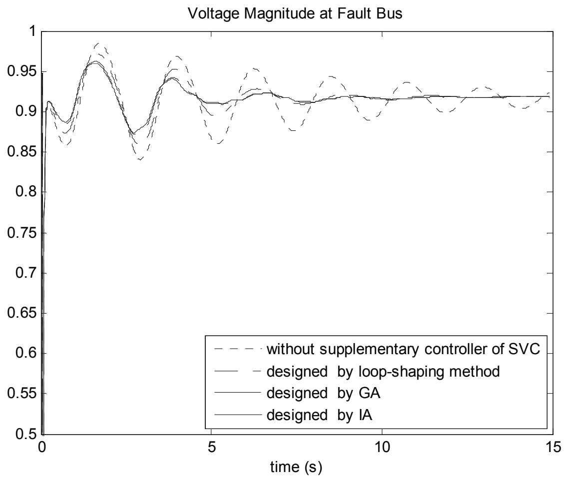

Fig. 6. The response of the system to a three-phase fault at bus 3.

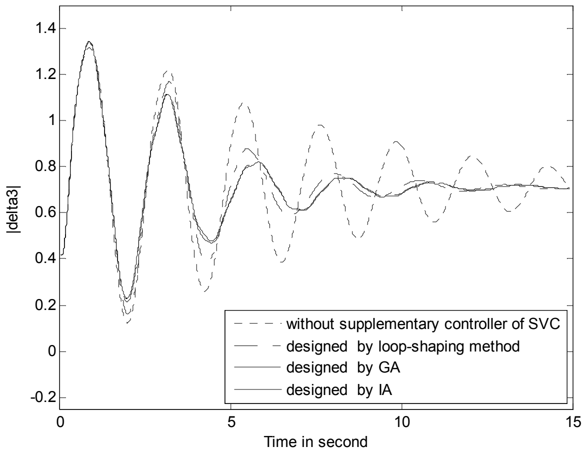

Fig. 7. The response of generator 3 to a three-phase fault.

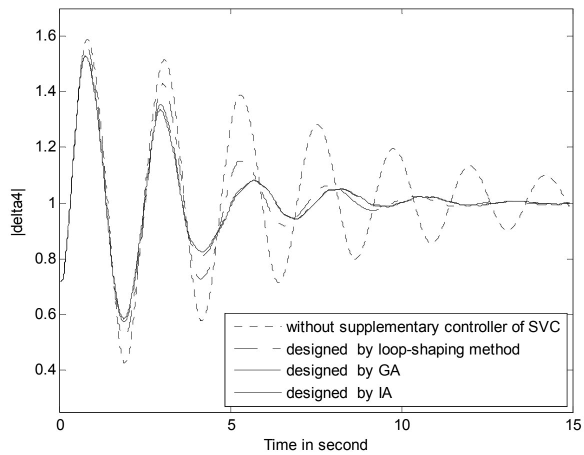

Fig. 8. The response of generator 4 to a three-phase fault.

5. CONCLUSION

This paper investigated the ability of IA in designing supplementary controller of SVC to damp the low frequency oscillations. For this the parameters of the controller is determined by IA using an eigenvalue-based objective function. Also, a simple GA and loop shaping method are applied to validate the results. To show the effectiveness of the designed controllers, a three-phase fault is applied at a bus. The simulation study shows that the designed controllers perform similar, but the one designed by heuristic algorithms (IA and GA) are easier to implement. Also, The obtained results show that the IA has the ability of solving the different power system problems.

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