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# Multi-objective VAr Planning with SVC Using Immune Algorithm and Guaranteed Convergence Particle Swarm Optimization

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**Abstract:** In this paper, the ability of Immune Algorithm (IA) is investigated for VAr planning with the Static Var Compensator (SVC) in a large-scale power system. To enhance voltage stability, the planning problem is formulated as a multi-objective optimization problem for maximizing fuzzy performance indices. The multi-objective VAr planning problem is solved by the fuzzy IA and the results are compared with those obtained by the fuzzy Genetic Algorithm (GA) and fuzzy Guaranteed Convergence Particle Swarm Optimization (GCPSO).

## 1. INTRODUCTION

Voltage collapse and other instability problems can be related to the system's inability to meet VAr demands (Kundur, 1994). Efforts have been made to find the ways to assure the security of the system in terms of voltage stability. Flexible AC transmission system (FACTS) devices are good choice to improve the voltage profile in a power system, which operates near the steady-state stability limit and may result in voltage instability. Taking advantages of the FACTS devices depends greatly on how these devices are placed in the power system, namely on their location and size.

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomena (Lee, *et al*., 1995; Lee and El-sharkawi, 2002, 2003; Lee, 2005). The ability of different algorithms is investigated by the authors in VAr planning by SVC based on single objective and multi-objective functions (Ebrahimi, *et al*., 2006; Farsangi, *et al*., 2006, 2007). Also, the ability of modal analysis is investigated where this method meets difficulties in placing SVC optimally (Ebrahimi, *et al*., 2006).

In the work carried out by Farsangi, *et al*., (2007) , the VAr planning problem is formulated as a multi-objective optimization problem for maximizing fuzzy performance indices, which represent minimizing voltage deviation, $RI^2$ losses and the cost of installation resulting in the maximum system VAr margin. The obtained results show that GA and GCPSO have good capability in solving the problem but GA gives better convergence characteristic. In view of this, this paper investigates the applicability of the IA in the VAr planning problem with SVC and the results will compared by GA and GCPSO.

## 2. OVERVIEW OF IA, GCPSO AND GA

A brief explanation of IA, GCPSO and GA is given below:

### *2.1 Immune Algorithm.*

IA has desirable characteristics as an optimization tool and offer significant advantages over traditional methods. The IA may be used to solve a combinatorial optimization problem.

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.

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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.

In IA, $n$ antibody 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. 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 iteration or when an antibody of maximal affinity is found.

### 2.2 Guaranteed Convergence PSO (GCPSO)

The GCPSO was introduced by Van den Bergh and Engelbrecht, 2002 to address the issue of premature convergence of PSO to solutions that are not guaranteed to be local exterma.

In PSO, each particle moves in the search space with a velocity according to its own previous best solution and its group's previous best solution. The dimension of the search space can be any positive integer. Each particle updates its position and velocity with the following two equations:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{1}$$

where $X_i(t)$ and $V_i(t)$ are vectors representing the position and velocity of the $i^{th}$ particle, respectively; and

$$V_{i,j}(t+1) = wV_{i,j}(t) + c_1 r_{1,j}(pb_{i,j} - X_{i,j}(t)) + c_2 r_{2,j}(gb_j - X_{i,j}(t)) \tag{2}$$

where $j \in 1,2,...,d$ represents the dimension of the particle; $0 \le w < 1$ is an inertia weight determining how much of the particle's previous velocity is preserved; $c_1$ and $c_2$ are two positive acceleration constants; $r_{1,j}, r_{2,j}$ are two uniform random sequences sampled from U(0, 1); $pb_i$ is the personal best position found by the $i^{th}$ particle; and $gb$ is the best position found by the entire swarm so far.

The modifications to the standard PSO involve replacing the velocity update (2) of only the *best* particle with the following equation:

$$V_{i,j}(t+1) = wV_{i,j}(t) - X_{i,j}(t) + pb_{i,j} + \rho(t) r_j \tag{3}$$

where $r_j$ is a sequence of uniform random numbers sampled from U(-1,1) and $\rho(t)$ is a scaling factor determined using:
$\rho(0) = 1.0$

$$\rho(t+1) = \begin{cases} 2\rho(t) & if\ \#successes > s_c \\ 0.5\rho(t) & if\ \#failures > f_c \\ \rho(t) & otherwise \end{cases} \tag{4}$$

where $s_c$ and $f_c$ are tunable threshold parameters.
Whenever the best particle improves its personal best position, the success count is incremented and the failure count is set to 0 and vice versa. The success and failure counters are both set to 0 whenever the best particle changes. These modifications cause the best particle to perform a directed random search in a non-zero volume around its best position in the search space.

### 2.3 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, 1989).

## 3. Problem Formulation

The goal is that to find the best SVC location and the level of compensation, which would result in the increase of system VAr margin. Increasing system VAr margin could be achieved by placing SVC considering the following objective functions:

*1) Active power loss*. The total power loss to be minimized is as follows:

$$P_L = \sum\left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right]Y_{ij}\cos\varphi_{ij} \tag{5}$$

where $V_i$ and $\delta_i$ are the magnitude and angle of voltage at bus *i*, and $Y_{ij}$ and $\varphi_{ij}$ are the magnitude and angle of the admittance of the line from bus *i* to bus *j*.

*2) Maximum voltage deviation*. To have a good voltage performance, the voltage deviation at each load bus must be made as small as possible. The voltage deviation to be minimized is as follows:

$$f = \max_{k\in\Omega}\left|V_k - V_{ref\,k}\right| \tag{6}$$

where $\Omega$ is the set of all load buses, $V_k$ is the voltage magnitude at load bus *k* and $V_{refk}$ is the nominal or reference voltage at bus $k$.

*3) Cost function of SVC.* The cost function for SVC in terms of (US$/kVAr) is given by the following equation:

$$C = 0.0003Q^2 - 0.3051Q + 127.38 \quad (7)$$

where $Q$ is MVAr size of SVC.

There are a number of approaches to solve the multi-objective optimization problem. Since SVC placement according to the multi-objective functions is difficult with an analytical method, a fuzzy logic technique is proposed in this paper to achieve a trade off between the objective functions. The multi-objective optimization problem is transformed into a fuzzy inference system (FIS), where each objective function is quantified into a set of fuzzy objectives selected by fuzzy membership functions.

The FIS is composed of fuzzification, inference engine, knowledge or rule base, and defuzzification. The fuzzification process is an interface between the real world parameters and the fuzzy system. It performs a mapping that transfers the input data into linguistic variables and the range of these variables forms the fuzzy sets. The inference engine uses the rules defined in a rule base and develops fuzzy outputs from the fuzzy inputs. The rule base includes the information given by the expert in the form of linguistic fuzzy rules, or experience gained in the process of experiment. The defuzzification is a reverse process of the fuzzification. It maps the fuzzy output variables to the real world, or crisp, variables that can be used in controlling a real world system.

In this paper, the three objective functions, the voltage deviation ($f$), the power loss ($P_L$) and installation cost ($C$) are inputs to the FIS and the output is an index of satisfaction or fitness achieved. The inputs are fuzzified by the membership functions shown in Figs. 1-3. The membership function of the output is shown in Fig. 4. The inference engine uses the rules defined in Tables 1-3 and develops fuzzy outputs from the fuzzy inputs. The fuzzy output is defuzzified by the Center of Gravity (COG) method to yield a crisp value for the level of satisfaction or fitness.

Tables 1-3 show the fuzzy rules for solving the problem where, G stands for good, M stands for moderate, B stands for bad, V stands for very and Ex stands for excellent.

**Table 1: Fuzzy rules**

Input 1 ($f$)

| | For $C$(Low) | G | M | B |
|---|---|---|---|---|
| Input 2 ($P_L$) | G | Ex | G | VB |
| | M | VVG | M | VB |
| | B | VG | VB | VVB |

**Table 2: Fuzzy rules**

Input 1 ($f$)

| | For $C$(Med) | G | M | B |
|---|---|---|---|---|
| Input 2 ($P_L$) | G | VVG | M | VB |
| | M | VG | B | VVB |
| | B | G | VVB | VVB |

**Table 3: Fuzzy rules**

Input 1 ($f$)

| | For $C$(High) | G | M | B |
|---|---|---|---|---|
| Input 2 ($P_L$) | G | VG | B | VVB |
| | M | G | VB | VVB |
| | B | M | VVB | VVB |

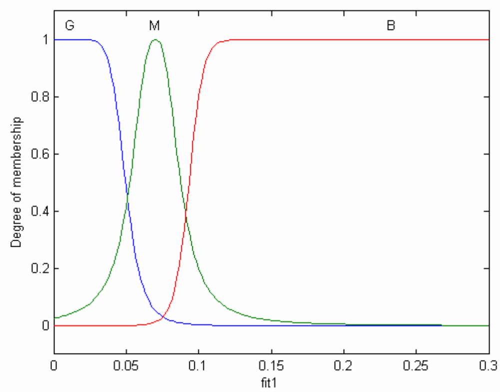


Fig. 1. Membership functions for Input 1, voltage deviation ($f$).

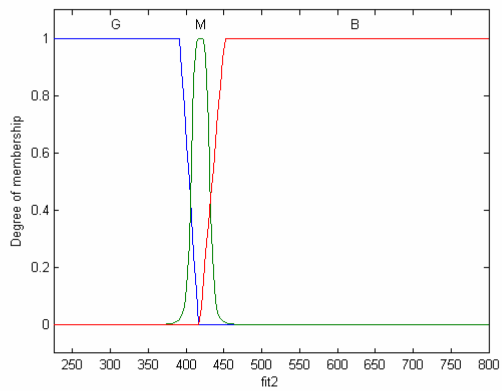


Fig. 2. Membership functions for Input 2, active power loss ($P_L$).

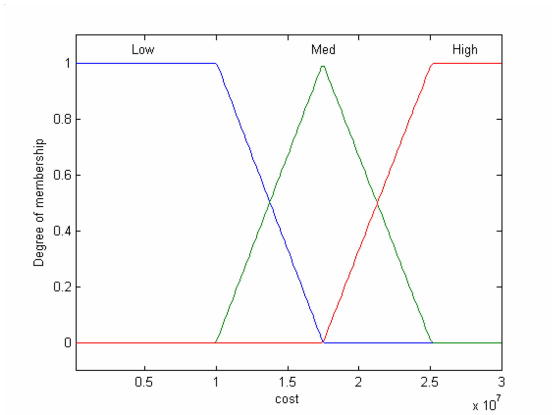


Fig. 3. Membership functions for Input 3, cost function (*C*).

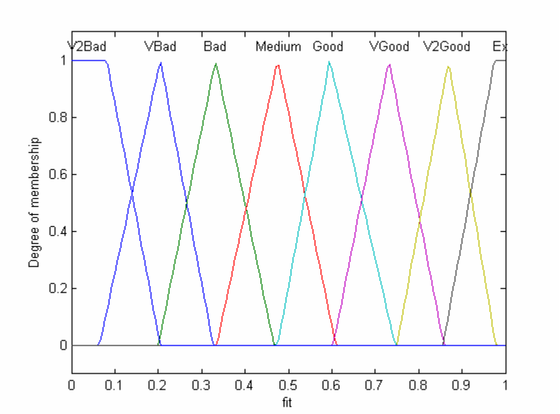


Fig. 4. Membership functions for output, the level of satisfaction (fitness).

## 4 . STUDY SYSTEM

**A 5-area-16-machine system:** The study system is shown in Fig. 5, consisting of 16 machines and 68 buses. This is a reduced order model of the New England (NE) New York (NY) interconnected system. The first nine machines are the simple representation of the New England system generation. Machines 10 to 13 represent the New York power system. The last three machines are the dynamic equivalents of the three large neighboring areas interconnected to the New York power system.

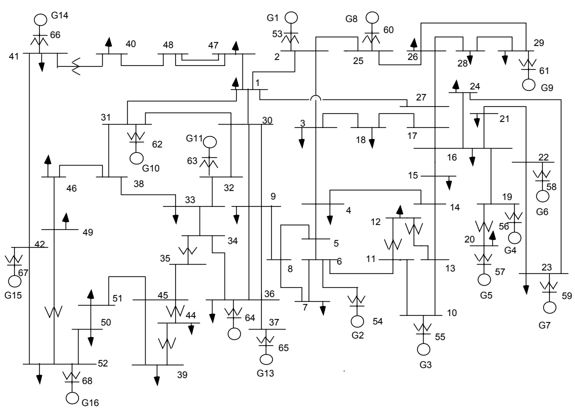

Fig. 5. Single line diagram of a 5-area study system.

IA incorporating the FIS is used to locate SVC in the power system shown in Fig. 5. The implementation is presented below:

Placing of SVC starts from an initial load. All loads are increased gradually near to the point of voltage collapse. A population of $n$ antibodies are generated randomly, where $n$ is considered to be 100. The goal of the optimization is to find the best location of SVC where the optimization is made on two parameters: its location and size. Therefore, a configuration is considered for each antibody as a vector such as $[location, size]$.

During each generation, the antibodies are evaluated by the FIS. Then the best antibody is chosen (best fitness). In the current problem, the best antibody is the one that has maximum 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:

$$affinity = \frac{f(antigen)}{f(antibody)} \tag{8}$$

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 70.

To locate an SVC with IA, suitable buses are selected based on 10 independent runs under different random seeds. At the end of the 10 independent runs, the following results are observed by the fuzzy IA: 90% of the results show that the SVC should be placed at bus 1 with 546 MVAr size; 10% of the results show that the SVC should be placed at bus 1 with 548 MVAr.

Based on the work carried out by Farsangi, *et al.* (2007), the following results are obtained by fuzzy GA and GCPSO:
40% of the results obtained by GCPSO show that the SVC should be placed at bus 1 with 546 MVAr size; 30% of the results show that the SVC should be placed at bus 42 with 720 MVAr size and 30% of the results show bus 41 with size 1544 MVAr.

But 60% of the obtained results by GA reveal that the SVC should be placed at bus 1 with 546 MVAr size, 10% of results show that the SVC should be placed at bus 41 with 1646 MVAr size and 30% of results show that the SVC should be placed at bus 37 with 1042 MVAr size. The obtained results are summarized in Table 4. This Table shows that the best solution is bus 1 with 546 MVAr size.

The results obtained by three algorithms are averaged over 10 independent runs. The average best-so-far of each run are recorded and averaged over 10 independent runs. To have a better clarity, the convergence characteristics in finding the location and size of an SVC is given in Fig. 6 for three algorithms. This figure shows that the convergence of IA is much better than the GA and GCPSO for the current problem.

The voltage profiles when the system is heavily stressed are shown in Figs. 7-8, for before and after placing the SVC.

**Table 4. The obtained results by IA, GCPSO and GA with fuzzified objective functions.**

| SVC Placement | | MVAr Size | Maximum voltage deviation | losses | Cost | fit |
|---|---|---|---|---|---|---|
| IA | **bus 1** | **546** | **0.0506** | **396** | **$2.73*10^7$** | **0.516** |
| | bus 1 | 548 | 0.0509 | 396 | $2.75*10^7$ | 0.514 |
| GCPSO | **bus 1** | **546** | **0.0506** | **396** | **$2.73*10^7$** | **0.516** |
| | bus 42 | 720 | 0.127 | 498 | $4.59*10^7$ | 0.5 |
| GA | **bus 1** | **546** | **0.0506** | **396** | **$2.73*10^7$** | **0.516** |
| | bus 37 | 1042 | 0.1 | 478 | $4.17*10^7$ | 0.5 |

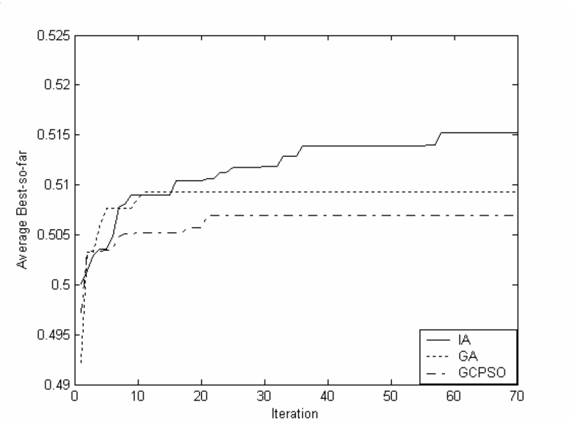


Fig. 6. Convergence characteristic of IA, GCPSO and GA on the average best-so-far in finding the solution, placement of SVC at bus 1.

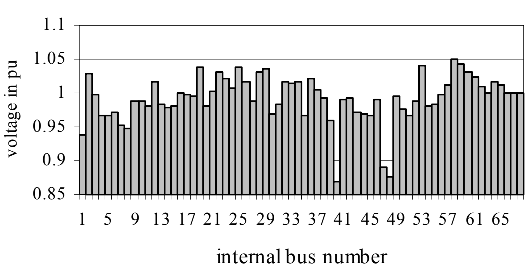


Fig. 7. Bus voltage magnitude profile when system is heavily stressed.

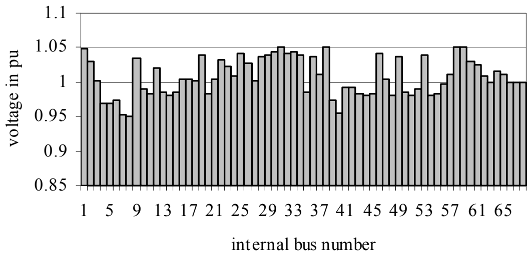


Fig. 8. Bus voltage magnitude profile of the stressed system after placing a 546 MVAr, SVC at bus 1.

Fig. 8 shows that the voltage profile has been improved perfectly. The maximum voltage in Fig. 8 is 1.05 and the minimum voltage is 0.949 at bus 8. As it can be seen in Table 4 (the third column) the other solutions found by GA and GCPSO are not good due to having a voltage deviation for PQ bus more than 0.05.

## 5. CONCLUSION

In this paper the ability of IA with fuzzy objective functions is investigated to place SVC in a power system, where VAr planning is based on the reduction of the system losses, reduction of voltage deviations and cost function. The results obtained by the IA, are compared by GA and GCPSO. When the population size is 100, the three algorithms find bus 1 but the convergence characteristics show that IA has a great ability in solving power system problems.

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