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SVC MULTI-OBJECTIVE VAR PLANNING USING SFL

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Abstract- In this paper, Shuffled frog leaping (SFL) algorithm is used for VAr planning with the Static Var Compensators (SVC) in a large-scale power system. To enhance voltage stability, planning problem is formulated as a multiobjective optimization problem for maximizing fuzzy performance indices. The multi-objective VAr planning problem is solved by the fuzzy SFL and the results are compared with those obtained by the Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).

Keywords: Shuffled Frog Leaping, Low-Frequency Oscillations, Stability, PSS.

I. INTRODUCTION

Voltage collapse and other instability problems can be related to the system's inability to meet VAr demands [1]. 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. The ability of different algorithms is investigated by the authors in VAr planning by SVC based on single objective and multi-objective functions [2]-[3]. Also, the ability of modal analysis is investigated where this method meets difficulties in placing SVC optimally [2]. The work carried out by the authors in [3] used Particle Swarm Optimization (PSO), Guaranteed Convergence PSO (GCPSO) and Genetic Algorithm (GA) for multi-objective VAr planning by SVC.

This paper investigates the applicability of a new algorithm known as the Shuffled frog leaping (SFL) algorithm in the VAr planning problem with SVC. 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 results obtained by the SFL are compared with those obtained by the GCPSO PSO and GA in [3].

II. OVERVIEW OF SFL

In SFL the population of the frogs is divided into different groups referred to as memeplexes when searching for the location that has the maximum amount of available food. Each memeplexes has different cultures by performing a local search. Each frog has their own idea and can be influenced by the ideas of other frogs during the iterative shuffling process of memetic evolution following by passing he ideas among memeplexes in a shuffling process [4]-[9].

In the population based heuristic algorithms two common aspects can be recognized; exploration and exploitation. The exploration is the ability of expanding search space, 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.

The issue of exploration and exploitation is taken into account by a frog leaping rule for local search and a memetic shuffling rule for global information exchange.

By the above description, the principle of SFL can be summarized in Figure 1. As Figure 1 shows at the first step, n frogs $P=\{X_1, X_2, \ldots, X_n\}$) are generated randomly within the feasible space. For S-dimensional problems (S variables), the position of a frog ith in the search space is represented as $X_i=[x_1, x_2, \ldots, x_{iS}]^T$. The frog's position is evaluated using a suitable objective (fitness) function. After evaluating the frogs are sorted in a descending order according to their fitness. The frog with the global best fitness is identified as X_g. The entire group can be divided into m memeplexes, each of which consisting of n frogs, which satisfy $P=m\times n$.

The strategy of division is as follows: the first frog goes to the first memeplex, the second frog goes to the second memeplex, mth frog goes to the mth memeplex, and and (m +1)th frog goes back to the first memeplex, etc.

Within each memeplex, the frogs with the best and the worst fitness are identified as X_b and X_w, respectively. During memeplex evolution, the worst frog X_w leaps toward the best frog X_b, based on the following leaping rule

$$D = \text{rand}() \times c \times (X_b - X_w) + W \quad (1)$$

$$W = [r_1 w_{1,\max}, r_2 w_{2,\max}, \ldots, r_s w_{s,\max}]^T \quad (2)$$

$$X_w(new) = \begin{cases} X_w + D & \text{if } \|D\| \le D_{\max} \\ X_w + \dfrac{D}{\sqrt{D^T D}} D_{\max} & \text{if } \|D\| > D_{\max} \end{cases} \quad (3)$$

where rand() is a random number between 0 and 1; c is a constant chosen in the range between 1 and 2; $r_i (1 \le i \le S)$ is random number between -1 and 1; $w_{i,\max} (1 \le i \le S)$ is the maximum allowed perception and action uncertainties in the ith dimension of the search space and D_{max} is the maximum allowed distance of one jump. If the repositioning process produces a frog with better fitness, it replaces the worst frog. Otherwise, the process is repeated with respect to the global best frog (X_g) with the best fitness across the memeplexes (X_g replaces X_b). In case of no improvement, a new frog within the feasible space is randomly generated to replace the worst frog. The evolution process is continued until the termination criterion is met. The termination criterion could be the number of iterations or when a frog of maximal fitness is found.

```
Pesedo code of shuffled frog leaping:
Start:
Randomly generate a population (P) of solution (frog):
For i=1 to number of iteration;
Devided P into m memplex;
Determine the best and worst frogs;
Repeat
Improve the Worst frog position using equation (1) - (3);
Until a specific number of iterations is satisfied:
End for;
End for;
Shuffled the memplexes;
Sort the population n in descending order of their fitness;
Check if completion = true
End
```

Figure 1. The pseudo code of the SFL algorithm

III. PROBLEM FORMULATION

The VAr planning problem using SVC can be formulated by considering a number of different objective functions, i.e., multi-objective functions. They include in this paper reduction of voltage deviation, reduction of the active power loss, and reduction of installation cost.

A. Multi-objective Functions

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. System VAr margin can be evaluated by stressing the system gradually from an initial operating state until the state of critical voltage stability is reached. This can be done by increasing all loads gradually close to the point of voltage collapse. Increasing system VAr margin could be achieved by placing SVC considering following objective functions:

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

$$P_L = \sum \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j) \right] Y_{ij} \cos\varphi_{ij} \quad (4)$$

where V_i and δ_i are the magnitude and angle of voltage at bus i, and Y_{ij} and φ_{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 (to keep the voltage between 0.95- 1.05 per unit), the voltage deviation at each load bus must be made as small as possible. The voltage deviation to be minimized is as follows:

$$f = \max_{k \in \Omega} \left| V_k - V_{ref\,k} \right| \quad (5)$$

where Ω 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:

$$C = 0.0003Q^2 - 0.3051Q + 127.38$$

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 Figures 2-4. The membership function of the output is shown in Figure 5. 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. For example in Table 1 for low cost (C(Low)) if f is good (G) and P_L is good (G) therefore the level of satisfaction (fitness) is excellent (Ex). In Tables 1-3, 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

	For C(Low)	Input 1 (f): G	M	B
Input 2 (P_L)	G	Ex	G	VB
	M	VVG	M	VB
	B	VG	VB	VVB

Table 2. Fuzzy rules

	For C(Med)	Input 1 (f): G	M	B
Input 2 (P_L)	G	VVG	M	VB
	M	VG	B	VVB
	B	G	VVB	VVB

Table 3. Fuzzy rules

	For C(High)	Input 1 (f): G	M	B
Input 2 (P_L)	G	VG	B	VVB
	M	G	VB	VVB
	B	M	VVB	VVB

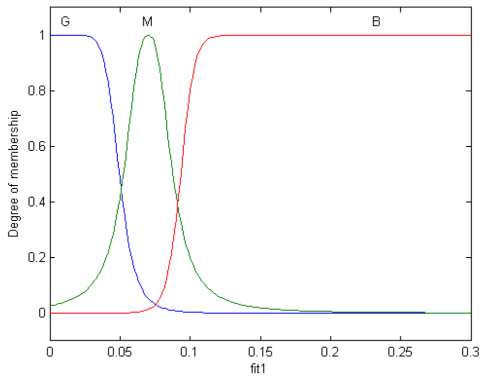

Figure 2. Membership functions for Input 1, voltage deviation (f)

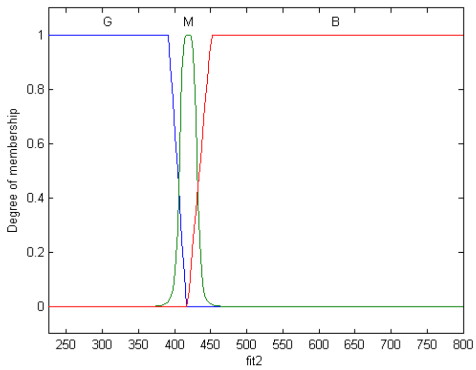

Figure 3. Membership functions for Input 2, active power loss (P_L)

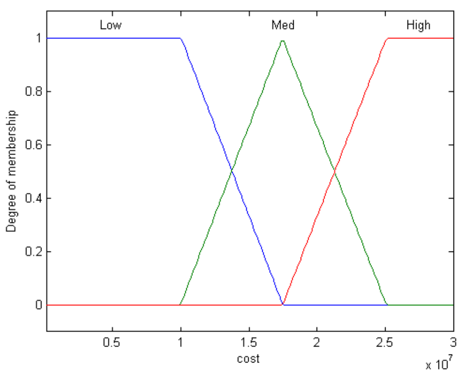

Figure 4. Membership functions for Input 3, cost function (C)

IV. STUDY SYSTEM

A 5-area-16-machine study system is shown in Figure 6, which consists 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 through 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.

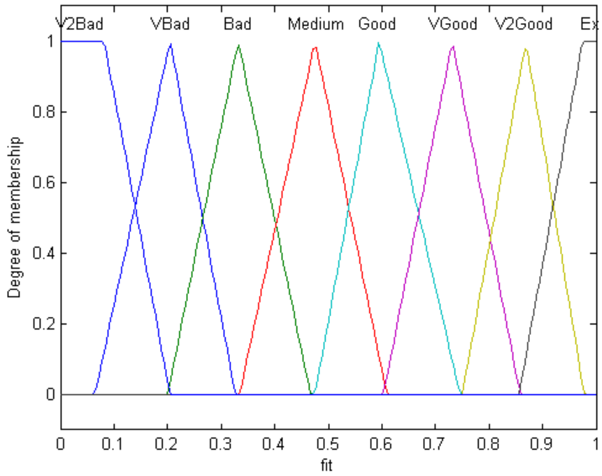

Figure 5. Membership functions for output, the level of satisfaction (fitness)

SFL incorporating the FIS is used to locate SVC in the power system shown in Figure 6. 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. In the SFL algorithm, an initial population is generated randomly where P is selected to be 100. The number of memplex is considered to be 10 with 10 frogs and the number of evaluation for local search is set to 10. 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. The initialization is made on the position randomly for each frog.

Each particle in the population is evaluated by the FIS, searching for the frogs associated with the best satisfaction (best fitness). Then the best frogs are chosen. In the current problem, the best frog is the one that has maximum fitness.

Based on Figure 1 the local search and shuffling processes (global relocation) continue until the last iteration is met. In this paper, the number of iteration is set to be 70.

To locate an SVC with fuzzy SFL, suitable buses are selected based on 10 independent runs under different random seeds. All 10 independent runs found bus 1 with 546 MVar size for SVC placement. In other words, 100% of the results show that the SVC should be placed at bus 1 with 546 MVAr size.

Now the results obtained by SFL is compared by our obtained results by GCPSO, standard PSO and GA in [3].

As it is reported in [3] at the end of the 10 independent runs, the following results are observed by the fuzzy GCPSO: 40% of the results 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.

Also, the following results are observed by the fuzzy PSO: 10% of results show that the SVC should be placed at bus 1 with 546 MVAr size and 40% of results show that the SVC should be placed at bus 41 and 50% of results show that the SVC should be placed at buses 42, 36, 37 and 52.

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.

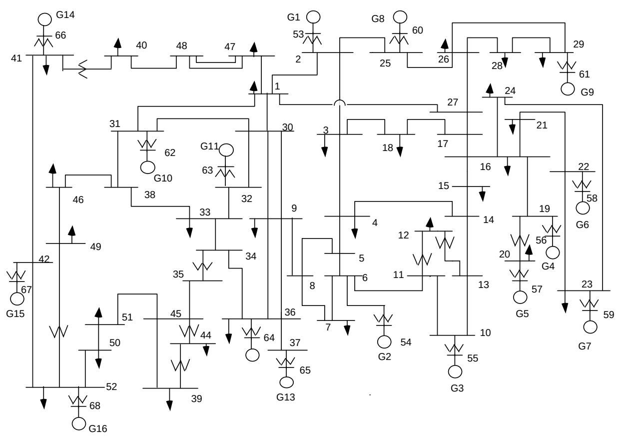

Figure 6. One-line diagram of a 5-area study system

Table 4. The obtained results by SFL, GCPSO, PSO and GA with fuzzified objective functions

SVC Placement		MVAr Size	Maximum voltage deviation	losses	cost	fit
SFL	bus 1	546	0.0506	396	$2.73*10^7$	0.516
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
PSO	bus 1	546	0.0506	396	$2.73*10^7$	0.516
	bus 41	1544	0.125	495	$4.95*10^8$	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

In the SFL algorithm, the best-so-far of each run is 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 Figure 7 for SFL algorithm. The reported convergence characteristics of GCPSO, PSO and GA in [3] are shown in Figure 8. These figures show that the convergence of SFL is much better than the GCPSO, PSO and GA in finding the solution. The voltage profiles when the system is heavily stressed are shown in Figs. 9-10, for before placing the SVC and after placing the SVC at bus 1with 546 MVAr size.

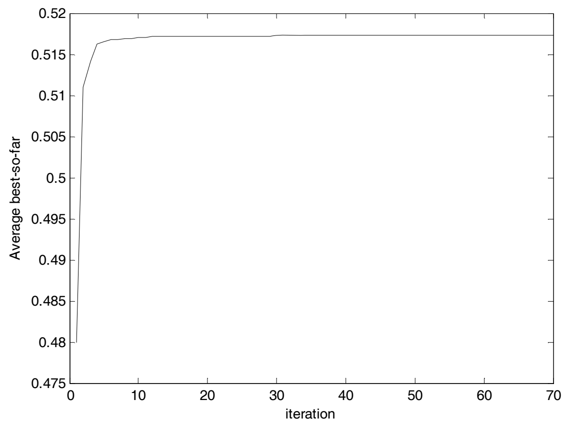

Figure 7. Convergence characteristics of SFL on the average best-so-far in finding the solution, placement of SVC at bus 1

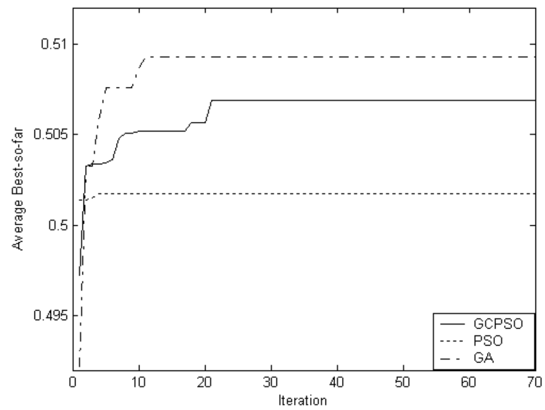

Figure 8. Convergence characteristics of GCPSO, PSO and GA on the average best-so-far in finding the solution, placement of SVC at bus 1

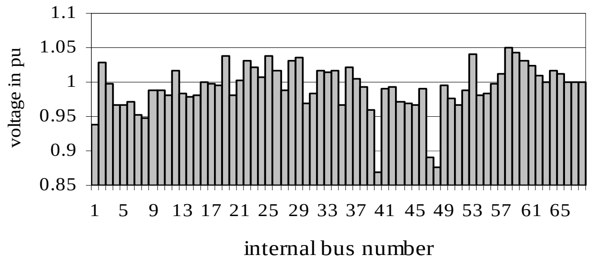

Figure 9. Bus voltage magnitude profile when system is heavily stressed

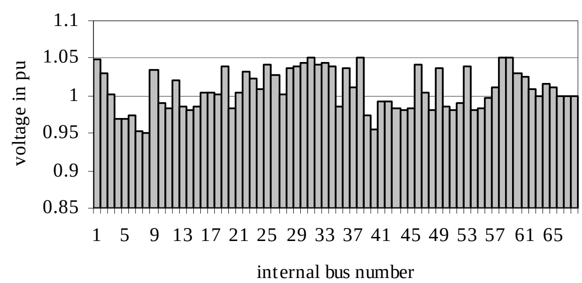

Figure 10. Bus voltage magnitude profile of the stressed system after placing a 546 MVAr SVC at bus 1

Figure 10 shows that the voltage profile has been improved perfectly. The maximum voltage in Figure 10 is 1.05 and the minimum voltage 0.949 is at bus 8.

V. CONCLUSIONS

In this paper the ability of a new algorithm known as SFL 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 are validated against those reported in [3] by GCPSO, PSO and GA. The results show that SFL has a good ability in solving the problem. Furthermore, the convergence characteristics of SFL show that the SFL has a better feature than GCPSO, PSO and GA in finding the solution.

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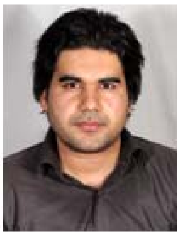
BIOGRAPHIES



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