Power system loading margin improvement with SVC using multi objective particle swarm optimization

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***Abstract*—Proper installation of flexible ac transmission systems (FACTS) in existing transmission networks can improve transmission system loading margin (LM) to a certain degree and reduce network expansion cost. In this paper, Particle Swarm Optimization (PSO) is used to determine which buses need static var compensator (SVC) installation. Maximum LM and minimum SVC installation cost composed into the multi-objective function the optimal LM enhancement problem is formulated as a multi-objective optimization problem (MOP) and solved by using the fitness sharing multi-objective particle swarm optimization (MOPSO) algorithm. The proposed method is validated on the IEEE 30-bus power system.**

***Index Terms*— Continuation power flow, loading margin, static voltage stability.**

I.INTRODUCTION

UNDER urgency to diminish the harms from environmental deterioration, one of the recently focused a research in the power industry is to make the existing transmission networks sufficiently utilize their capability in power transfer [1]–[3]. Through detailed studies, voltage instability was found to be the main factor responsible for several blackout events in the recent years [4]. As an index to indicate the level of static voltage stability of a transmission system, the loading margin (LM) or voltage stability margin (VSM), representing the maximum power that can be transferred between generators and loads before voltage collapse point achieved is generally measured in system planning [5], [6]. The optimal flexible ac transmission systems (FACTS) installation had been researched and discussed widely and several strategies were proposed. In general, the studies are oriented towards technical, economic, or both concerns. In technical concerns, the method proposed in [3] practically installed different types of FACTS devices on different locations to identify the increase of LM. While in [7], a two-stage SVC installation method is proposed. In stage one, LM is increased on a step-by-step basis and, in each step, to provide sufficient reactive power from an SVC installation, the location and its capacity are determined by using a genetic algorithm (GA), and, in stage two, under different contingencies the control signals to the SVC installation are determined based on various stability indices. The method proposed in [8] used GA to determine the locations and capacities for the respective installations of various types of FACTS devices for LM enhancement. While in [9], modal analysis (MA) technique and a guaranteed convergence particle swarm optimization (GCPSO) algorithm are used to determine the locations for SVC installation and the capacities to enhance LM. With the compensation of SVC, TCSC, and UPFC installations, in [10], the singular value/eigenvalue decomposition analysis of the load-flow Jacobian and the controllability characteristics of an equivalent state model are used to study the voltage instability phenomenon as well as to assess the potential for small-signal voltage stability improvement. Considering N_1 contingencies, in [11], tangent vector technique and reactive power sensitivity index were adopted as reference indices to point out the locations suitable for installations of the parallel and series FACTS devices. As specific contingencies are identified to be the main factors that result in voltage instability, [12] expressed N_1 line outages with stochastic model and used MA to expect the total participation in all critical modes (TPCM) index value for each bus. The bus with the biggest TPCM index value is selected for a STATCOM installation. On the other hand, in economic concerns, the total FACTS installation and generation costs were taken as the objective function in [13] and [14], and GA was used to make the decision where to install FACTS devices. The method proposed in [15], comprised of the tabu search (TS) and a nonlinear programming method, was used to optimize the FACTS devices investment and recovery. While the method developed in [16] with the proposed performance indices of real power flows was used to seek the optimal locations for FACTS installation.

Under the existing FACTS devices installed, in [17], the minimum generation cost-based OPF was solved using the proposed hybrid of TS and simulated annealing (SA) algorithm. While in [18], an optimal approach comprised of CPF and OPF techniques for UPFC installation was proposed to minimize the total generation and installation cost Dealing with both concerns simultaneously in the LM enhancement problem for deriving optimal FACTS installation, in [19], the proposed method linearly composed voltage security, system loss, capacities for STATCOM installation and LM into a single-objective function, which was solved by using a PSO algorithm. While in [20] and [21], a single objective function was linearly composed of the installation costs for various types of FACTS devices (UPFC, TCSC, and SVC), system securities, loss and voltage stability indices. The problem was solved by PSO in [20] and GA in [21]. Besides, to possibly reveal the variety of solutions, the optimal SVC installation problem for LM enhancement is formulated as an MOP. Reference [22] applied a multi-objective genetic algorithm (MOGA) to the combinatorial optimization problem with the multi-objective function composed of minimum FACTS installation cost and allowable system security limits. The results obtained to release the threats from low voltage and line congestion include the types of FACTS devices used, the installation locations and capacities. While in [23], the minimum generation costs and allowable system security limits are involved in the multi-objective function, and a bacterial swarming algorithm (BSA) is used to determine the installation locations and capacities for various types of FACTS devices (TCSC, TCPST, TCVR, SVC). The method proposed in [24] composed maximum LM, minimum system loss and voltage deviations at PQ buses into the multi-objective function, and an MOPSO method was used to solve for the locations and capacities for one SVC and one TCSC installations. From previous reviews, a FACTS installation problem can adopt linearization approaches, or methods with more flexibility including heuristic models and evolutional algorithms. In the paper, PSO technique is used to determine which buses need SVC installation, and the LM enhancement problem to determine the capacity of each SVC installation and generation pattern [6] is formulated as an MOP with maximum LM and minimum SVC installation cost involved in the multi-objective function. The fitness sharing MOPSO algorithm is used here.

II. PROBLEM FORMULATION

A. *Multi-Objective Optimization Problems*

When trying to solve an MOP, not only trying to look for one single solution but a set of trade-off solutions is the target of the solution algorithm and the one that will be chosen will depend on the needs of the decision maker. An MOP can be defined as

$$\begin{aligned} \text{Min} \quad & f(u) = [f_1(u), f_2(u), \ldots\ldots f_k(u)]^T \\ \text{S.t} \quad & h(u) = 0 \qquad (1) \\ & g(u) \leq 0 \end{aligned}$$

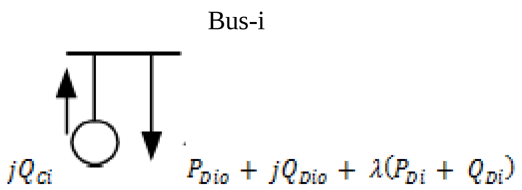

Fig. 1. PQ bus with an SVC installation.

where multi-objective function f includes $k(k \geq 2)$ objective functions, constraints $h(u)$ and $g(u)$ are equality and inequality functions, and is control variables. In order to optimize the vector function, the concepts tied to an MOP called "domination" and "non domination" are defined as [25]: *1) Solution u_1 is said to dominate solution u_2, if and only if u_1 is not worse than u_2 in all objectives and u_1 is strictly better than u_2 in at least one objective. 2) Among a set of solutions P, the non dominated set of solutions P' are those that are not dominated by any member of the set P.* If within the definition the set of solution P is replaced by the feasible search space F $(P = F)$, then the set of solutions in P' will be what is called Pareto-optimal set or Pareto front.

B. *Problem Formulation for Loading Margin Enhancement*

Let Q_{ci} be a regulable reactive power provided by the SVC at bus i and its range is set to: $-Q_C \leq Q_{ci} \leq Q_C$ .Fig. 1 shows the equivalent injection for a PQ bus with an SVC installation. Employing CPF technique to formulate the LM enhancement problem and letting λ, $\lambda \geq 0$, be the loading factor, λ = 0 for base load, the real and reactive power balance equations on bus i are expressed as

$$\sum_{j=1}^{n} P_{ij} + P_{io} - \lambda(\Delta P_{Gi} - \Delta P_{Di}) = 0 \qquad (2)$$

$$\sum_{j=1}^{n} Q_{ij} + Q_{io} + \lambda(\Delta Q_{Di}) + Q_{ci} = 0 \qquad (3)$$

$P_{io} = -P_{Gio} + P_{Dio}$ and $Q_{io} = -Q_{Gio} + Q_{Dio}$ are the base real and reactive power injections for the generator and load at bus i , and ΔP_{Gi} , and ΔP_{Di}, and ΔQ_{Di} are the generation increment and loading level. In the paper, the loading level is set to the base load such that the power factors are fixed as load changed with λ. The real and reactive power flows are

$$P_{ij} = V_i^2 G_{ij} - V_i V_j (G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij}) \qquad (4)$$

$$Q_{ij} = -V_i^2 (B_{ij} + B_{sh}) - V_i V_j (G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij}) \qquad (5)$$

The power flow balance (2) and (3) are expressed in an equality functional vector as follows:

$$h(x, u, \lambda) = 0 \qquad (6)$$

where system variables vector $x = [\theta \quad V]^T$ including bus voltage magnitudes and phase angles, and control variables vector $u = [\ \Delta P_G \ Q_C\ ]^T$ including the generation increments (or generation pattern) and reactive power injections Q_C of all SVC installations. Also, the inequality constraints that should be satisfied with include the limits of real and reactive power generations, and the capacities of existing control devices (AVR, SC, OLTC) and SVC installations, expressed in an inequality functional vector as follows:

$$g(x,u,\lambda) \leq 0 \quad (7)$$

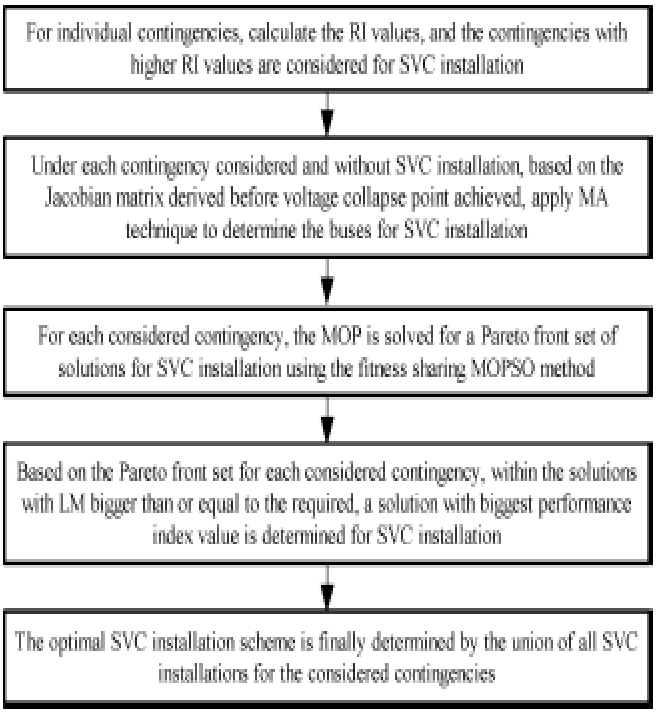

Fig. 2. Proposed LM enhancement strategy.

Based on specific control variables values, the maximum loading factor λ^* can be calculated using CPF process and the LM is derived as $\lambda^* \sum_{\forall i} \Delta P_{Di}$. The objective functions include maximum system LM (represented as), denoted as f_1, and minimum SVC installation cost, denoted as f_2. The two objective functions are integrated into a multi-objective function, expressed as a functional vector in the following:

$$f = [f_1 \ \ f_2]^T \quad (8)$$

If five years is the lifetime for an SVC installation, the operating cost (US$/h) for all SVC installations is [27]

$$f_2 = \frac{\sum_{\forall i}\left(0.0003{Q_{ci}}^2 - 0.3051Q_{ci} + 127.38\right)10^5 . Q_{ci}}{(5.8760)} \quad (9)$$

From (2) to (9), the LM enhancement problem with SVC installation is formulated as an MOP as follows:

$$\begin{aligned} &Min && f \\ &S.t && h(x,u,\lambda) = 0 \\ & && g(x,u,\lambda) \leq 0 \\ & && 0 \leq \lambda \end{aligned} \quad (10)$$

In the paper, the MOP for each considered contingency is solved by using the fitness sharing MOPSO algorithm, and from the obtained Pareto front set, a solution with $\lambda^* \geq \lambda_{req}$ and maximum performance index value f_1/f_2 is determined for SVC installation, where λ_{req} represents the required LM.

III. MOP-BASED SVC INSTALLATION STRATEGY

The LM enhancement strategy for SVC installation proposed in the paper is shown in Fig. 2. The key approaches used to realize the strategy are introduced as follows.

Multi-Objective Optimization Problem Solution Method

In the algorithm, particle position and velocity are updated using the following two equations [9]:

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (11)$$

$$v_{i,j}(k+1) = wv_{i,j}(k) + c_1 r_{1,j}\left(pbest_{i,j} - x_{i,j}(k)\right) + c_2 r_{2,j}(gbest_j - x_{i,j}(k)) \quad (12)$$

$X_i(k)$ and $V_i(k)$ represent the position and velocity of particle i at iteration $k. x_{i,j}$. Is the jth entry of $X_i(k)$. $v_{i,j}$ is the jth entry of V_i that denotes the velocity of $X_i(k)$; $0 \leq w \leq 1$ is an inertia weight determining how much the particle's previous velocity is preserved; c_1 and c_2 are two positive acceleration constants; $r_{1,j}, r_{2,j}$, are random numbers sampled from uniform distribution $U(0,1)$; $pbest_i$ and $gbest_j$ are the personal best position of particle i and the best position in the entire swarm, respectively. The fitness sharing technique [25] is used to modify the PSO into an MOPSO for solving the MOP described above. The fitness sharing scheme is to distribute a population of particles along a set of resources. When a particle is sharing resources with other particles, its fitness f_i is degraded proportional to the number and closeness to particles that surround it. If maximum objective is the target of the problem, the fitness sharing for particle is defined as

$$fs_i = \frac{f_i}{\sum_{k=1}^{NP} sh_i^k} \quad (13)$$

A bigger fitness sharing represents that the particle is distant from the swarm. On the other hand, while the target is to seek a minimum objective, the fitness sharing is defined as

$$fS_i = f_i \sum_{k=1}^{NP} Sh_i^k \quad (14)$$

where Sh_i^k denotes the sharing factor that measures the similarity from particles i to k by a distance d_i^k.function . When the particle is averagely more distant from other particles, a smaller sharing factor takes place

$$Sh_i^k = \begin{cases} 1 - (\frac{d_i^k}{\sigma})^2 & if\ d_i^k < \sigma \\ 0, & otherwise \end{cases} \quad (15)$$

And

$$d_i^k = \sum_j \left(\frac{x_{i,j} - x_{k,j}}{x_j^{max} - x_j^{min}} \right)^2 \quad (16)$$

where σ denotes the distance for the particles to remain distant from each other and j indexing variables in particle x. σ is set on a case-by-case basis. A particle with the best fitness sharing will take the position to guide the swarm into the next generation. With the fitness sharing scheme involved in the solution process, the determination of $gbest$ in the traditional PSO algorithm is changed to

$gbest = the\ pbest$ of the particle with maximum (or minimum) fitness sharing.

Fig. 3 shows the fitness sharing MOPSO algorithm used to find a Pareto front set of solutions for SVC installation under each considered contingency. The use of PSO technique is to guide the search with help of fitness sharing to spread the particles along the Pareto front. Fitness sharing will help to maintain diversity between solutions, and thus particles within high populated areas in the objective space will be less likely to be followed. In each iteration, the best particles found (those not dominated) will be inserted into an external repository. This repository will help to guide the search for the next generations and maintain a set of not dominated solutions until the end of the run, which form the Pareto front set.

Referring to the LM enhancement strategy proposed in Fig. 2, after the Pareto front set for each considered contingency is derived, within the solutions with $\lambda^* \geq \lambda_{req}$, a solution that has maximum performance index f_1/f_2 value is specified as the SVC installation for the contingency. Finally, the optimal

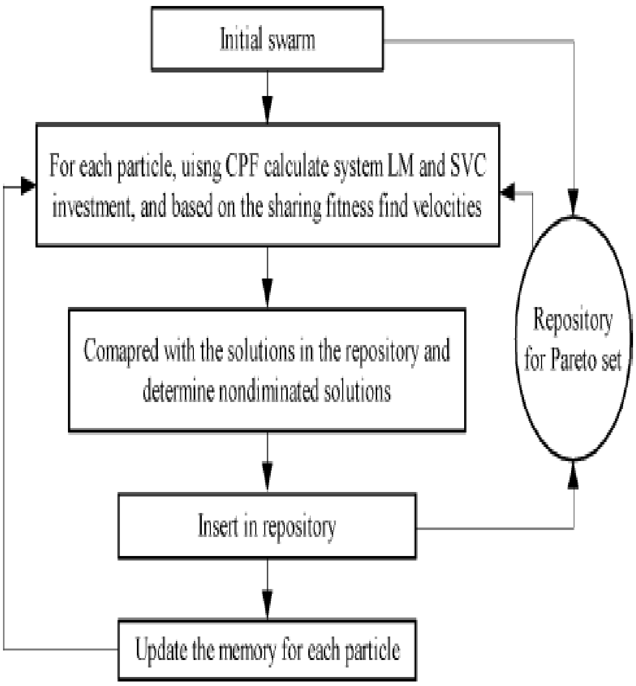

Fig. 3. Fitness sharing MOPSO algorithm.

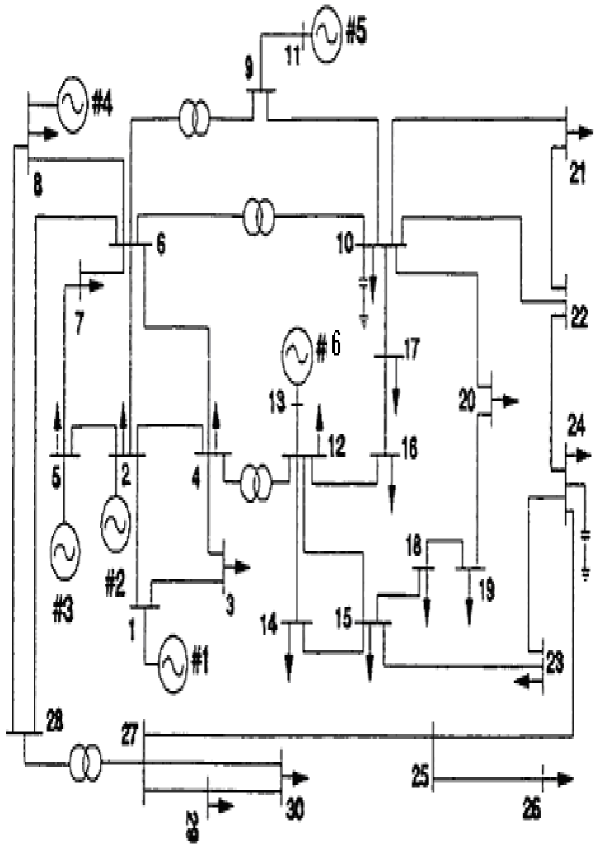

Fig. 4. Modified IEEE 30-bus reliability test system.

SVC installation is resulted from the union of the SVC installations for all considered contingencies. It is conceivable that, compared to the SVC installation for each contingency, the optimal SVC installation would have bigger SVC units number, each SVC installation with bigger or equal capacity.

IV. TEST RESULTS AND DISCUSSIONS

The Optimal Power Flow (OPF) is a highly non-linear, large scale optimization problem due to large number of variables & constraints. OPF with Fuel cost minimization as objective function is formulated as a single objective optimization case. The location of SVC controller and the setting of their control parameters are optimized by a particle Swarm Optimization (PSO) to improve the performance of the power network. Two objective functions are considered as the indexes of the system performance maximization of system loadability in system security margin and minimization of total generation fuel cost is multi objectives optimization case. The algorithm is implemented using Matlab® 2008a and is tested for its robustness on a standard IEEE 30 bus system. The network data is shown in Appendix A. The network consists of 6 Generator buses, 21 load buses & 41 lines, of which 4 lines are due to tap setting transformers. The total load on the network is 283.4 MW. The algorithms have been implemented on a personal computer with 2.44 GHz Intel core 4 processor and 2 GB RAM.

TABLE I
DATA FOR TRANSMISSION LINES

From Bus	To Bus	Resistance (p.u.)	Reactance (p.u.)	Half line charging susceptance(p.u.)	Transformer tap
1	2	0.0192	0.0575	0.0264	1
1	3	0.0452	0.1852	0.0204	1
2	4	0.057	0.1737	0.0184	1
3	4	0.0132	0.0379	0.0042	1
2	5	0.0472	0.1983	0.0209	1
2	6	0.0581	0.1763	0.0187	1
4	6	0.0119	0.0414	0.0045	1
5	7	0.046	0.116	0.0102	1
6	7	0.0267	0.082	0.0085	1
6	8	0.012	0.042	0.0045	1
6	9	0	0.208	0	1.0155
6	10	0	0.556	0	0.9629
9	11	0	0.208	0	1
9	10	0	0.11	0	1
4	12	0	0.256	0	1.0129
12	13	0	0.14	0	1
12	14	0.1231	0.2559	0	1
12	15	0.0662	0.1304	0	1
12	16	0.0945	0.1987	0	1
14	15	0.221	0.1997	0	1
16	17	0.0824	0.1932	0	1
15	18	0.107	0.2185	0	1
18	19	0.0639	0.1292	0	1
19	20	0.034	0.068	0	1
10	20	0.0936	0.209	0	1
10	17	0.0324	0.0845	0	1
10	21	0.0348	0.0749	0	1
10	22	0.0727	0.1499	0	1
21	22	0.0116	0.0236	0	1
15	23	0.1	0.202	0	1
22	24	0.115	0.179	0	1
23	24	0.132	0.27	0	1
24	25	0.1885	0.3292	0	1
25	26	0.2544	0.38	0	1
25	27	0.1093	0.2087	0	1
28	27	0	0.396	0	0.9581
27	29	0.2198	0.4153	0	1
27	30	0.3202	0.6027	0	1
29	30	0.2399	0.4533	0	1
8	28	0.0636	0.2	0.0214	1
6	28	0.0169	0.0599	0.0065	1

TABLE II
BASE LOAD AND POWER SUPPLIES

Bus No	P Gen	Q Gen	P Load	Q Load	Voltage
1	0	0	0	0	1.05
2	0.5756	0	0.217	0.127	1.0338
3	0	0	0.024	0.012	1
4	0	0	0.076	0.016	1
5	0.2456	0	0.942	0.19	1.0058
6	0	0	0	0	1
7	0	0	0.228	0.109	1
8	0.35	0	0.3	0.3	1.023
9	0	0	0	0	1
10	0	0	0.058	0.02	1
11	0.1793	0	0	0	1.0913
12	0	0	0.112	0.075	1
13	0.1691	0	0	0	1.0883
14	0	0	0.062	0.016	1
15	0	0	0.082	0.025	1
16	0	0	0.035	0.018	1
17	0	0	0.09	0.058	1
18	0	0	0.032	0.009	1

19	0	0	0.095	0.034	1
20	0	0	0.022	0.007	1
21	0	0	0.175	0.112	1
22	0	0	0	0	1
23	0	0	0.032	0.016	1
24	0	0	0.087	0.067	1
25	0	0	0	0	1
26	0	0	0.035	0.023	1
27	0	0	0	0	1
28	0	0	0	0	1
29	0	0	0.024	0.009	1
30	0	0	0.106	0.019	1

V. OPTIMAL POWER FLOWS WITH PARTICLE SWARM OPTIMIZATION

In this case each particle would be including all control variables, i.e. 5 active powers of generators, 6 generator voltages, 4 transformer taps & 9 shunt capacitance values, location & sizing of SVC (Total 26 control variables in a particle). The particles length for unit active power outputs is 6 particles, generator voltage magnitude is 6 particles and both of them are treated as continuous control variables. As the transformer tap settings can take 17 discrete values each one is encoded using 6 particles & the step size is 0.0125 p.u. The bus shunt susceptance can take 6 discrete values each one is encoded using 6 particles, & the step size is 0.01 p.u. (on system MVA basis).

. *PARAMETERS*: Swarm size =60, Size of particle =26, Maximum Number of iterations=100, acceleration constants C1=C2=2.05, Inertia Weight (W) =1.2 & Constriction Factor (K) =0.7295.

MINIMIZATION OF TOTAL GENERATION FUEL COST & MAXIMIZATION OF SYSTEM LOADABILITY WITH PARTICLE SWARM OPTIMIZATION

TABLE.III
OPTIMAL SETTING OF CONTROL VARIABLES FOR OPF USING PSO (WITH &WITHOUT) SVC.

Variables	PSO without SVC devices	PSO with SVC devices
Slack	174.909	175.475
PG2	49.802	48.777
PG5	23.017	21.306
PG8	21.557	22.812
PG11	11.319	12.218
PG13	12.233	12.000
VG1	1.050	1.050
VG2	1.085	1.040
VG5	1.011	1.018
VG8	1.038	0.978
VG11	1.034	0.978
VG13	1.033	1.038
Tap 6-9	1.000	0.900
Tap 6-10	1.050	1.075
Tap 4-12	0.988	0.988
Tap 28-27	1.025	1.038
Shunt 10	0.050	0.100
Shunt 12	0.020	0.080
Shunt 15	0.030	0.060
Shunt 17	0.050	0.120
Shunt 20	0.100	0.120
Shunt 21	0.010	0.120
Shunt 23	0.050	0.120
Shunt 24	0.010	0.060
Shunt 29	0.050	0.120
Optimal fuel cost($/hr)	804.610	803.010
Time	223.89sec	226.57sec

Variable	Location	Value
SVC	18	0.068750

It is observed that fuel cost obtained when SVC is also considered as decision variable is better than that obtained without SVC .The fuel cost obtained without SVC is 804.610 ($/hr) .the fuel cost obtained with SVC placed at location 18th with its value as -0.093750 is 803.010 ($/hr).

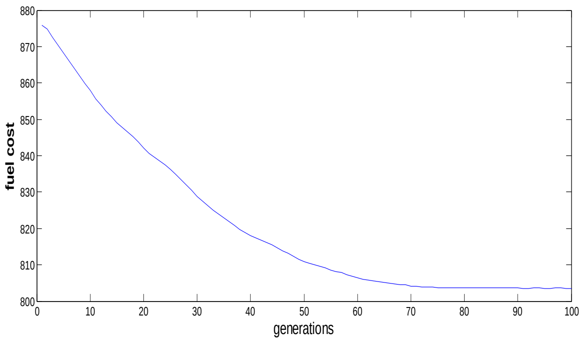

Fig 5 Convergence characteristic of PSO for OPF without SVC

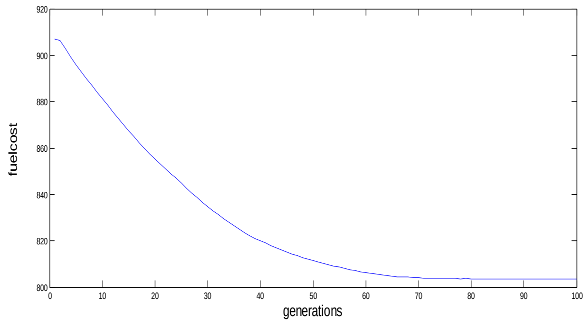

Fig 6 Convergence characteristic of PSO for OPF with SVC

As seen from table III PSO achieves the best result by placing of SVC controller in the IEEE 30-bus test system. Compared with the original IEEE 30-bus system in which SVC controller are not installed, Furthermore, the problem is handled as a multi-objective optimization problem and both fuel cost and system loadability are optimized using PSO (with& without) SVC. The maximal limit of the load factor is set at 1.5, which reflects a 50% percent increment of power demands. The variation of the load factor is allowed in the bound of [1, 1.5].

VI. CONCLUSION

From a long-term economic development point of view, it is expectable that regional or integral electric power demands will increase or change constantly. Besides, in the deregulated electrical power systems, due to open access to the transmission networks, various types and a large amount of power transactions would result in huge changing power flow. In this view, serious threats to power system operation security might occur. To improve the operation security of power systems while avoiding network expansion by building more transmission lines, it is a good choice to suitably install FACTS devices in existing networks such that they can accommodate more power transfer. The proposed MOPSO is then used to determine an optimal SVC installation scheme for the required LM with the SVC installation locations and capacities. From the test results, the achievement of the proposed strategy for SVC installation, that is well consistent with specific economic and technical concerns, is validated.

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