Comparative Study on the Application of Modern Heuristic Techniques to SVC Placement Problem

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***Abstract*—This paper investigates the applicability and effectiveness of modern heuristic techniques for solving SVC placement problem. Specifically, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Evolutionary PSO (EPSO) have been developed and successfully applied to find the optimal placement of SVC devices. The main objective of the proposed problem is to find the optimal number and sizes of the SVC devices to be installed in order to enhance the load margin when contingencies happen. SVC installation cost and load margin deviation are subject to be minimized. The proposed approaches have been successfully tested on IEEE 14 and 57 buses systems and a comparative study is illustrated. To evaluate the capability of the proposed techniques to solve large scale problems, they are also applied to a large scale mixed-integer nonlinear reactive power planning problem. Results of the application to IEEE 14 bus test system prove the feasibility of the proposed approaches and outperformance of PSO based techniques over GA.**

***Index Terms*—FACTS devices, SVC, Modern heuristic techniques, Evolutionary Programming, Genetic Algorithm, Particle Swarm Optimization, Evolutionary PSO**

I. INTRODUCTION

With the worldwide restructuring and deregulation of power systems, sufficient transmission capacity and reliable operation have become more valuable to both system planners and operators. Building new constructions to enhance the loadability of a network is very expensive and many constraints have to be satisfied. As a result, there is a significantly increased potential for the application of FACTS devices due to their important role in power system security enhancement. Among the FACTS devices, Static VAr Compensators (SVCs) are widely used around the world both for their capabilities and for their low maintenance costs. Although investment cost of SVCs are expensive but maintenance costs are low since the devices have no moving parts and repairs are minimal [1].

Basic Optimal FACTS Allocation problem has been solved by various optimization techniques and different objective functions [2]. In general optimal FACTS allocation problem is to determine the optimal size and location of new installed FACTS devices in order to optimize a specific objective function while considering variety of operating constraints. The main presented objective functions are system loadability maximization, minimization of overall operation cost, minimization of installation cost and congestion management.

Most of the mentioned works in [2] do not consider voltage security constraints, system operation and investment costs in an integrated formulation. A comprehensive formulation for Reactive Power Planning (RPP) problem including the allocation of FACTS devices is introduced in [3]. The problem is formulated as a large scale mixed integer nonlinear programming and the main objective is to make a trade-off between economy and security by determining the optimal combination of fast and slow controls (load shedding, new slow and fast VAR devices) during corrective and preventive control states. Metaheuristic techniques are used to solve the proposed problem and a comparative study on the performance of the optimization techniques is presented in [4,5].

An overview of modern heuristic techniques and specific applications of heuristic approaches to power system problems has been discussed in [6]. Some well-known modern heuristic techniques are Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS), Particle Swarm Optimization (PSO) and Evolutionary PSO (EPSO).

A GA algorithm is presented in [7] to optimally locate multiple-type FACTS devices in a power system where, four types of controllers were chosen and modeled for steady-state studies. Authors in [8] introduced a hybrid Genetic Algorithm and Successive Linear Programming (GA/SLP) to solve a voltage constrained VAR planning problem. It has been claimed that GA leads to better solution and disappears any divergence problem mentioned in [9].

Particle Swarm Optimization (PSO) is one of the Evolutionary Computation (EC) techniques [10], which has been proved as a powerful tool and outperforms the other heuristic methods. The main features of PSO are its simplicity, robustness, effectiveness in performing difficult optimization tasks and ability to treat both continuous and discrete variables. It has been applied in various power system problems and successful application in RPP problem is reported [11-14].

Evolutionary PSO (EPSO) was first developed by Miranda, *et al.* [15] and combines conventional PSO with the evolutionary strategy. EPSO puts together the concepts of Evolution Strategies (ES) and of PSO. The particles are move according to the conventional PSO movement rule, but the strategic parameters are selected according to ES procedure. Therefore, it is expected that the exploratory power of PSO and self-adaptation power of ES is obtained. Successful application in power system problems is reported in [16, 17] while the results are compared with conventional PSO and SA.

This paper aims to evaluate and compare the performance of the above mentioned modern heuristic techniques in solving optimal SVC placement problem. First, a formulation is introduced to find the optimal allocation of SVC devices in order to minimize total cost while deviation from desired load margin is minimized during base case and contingency states. Then, the above mentioned modern heuristic techniques are used to find the near optimal solutions for the proposed problem. A comparative study is worked out to better compare the performance of the solution techniques.

The rest of this paper is organized as follows: Section II describes the problem formulation. Section III, introduces the modern heuristic techniques used in this paper and explains how solution techniques have been applied in the proposed problems. As the IEEE-14 and IEEE-57 bus systems are tested to demonstrate the effectiveness of the proposed method, section IV is devoted to present the numerical study results.

II. PROBLEM FORMULATION

The objective function of the proposed SVC placement problem is to minimize total cost, including investment cost of SVC devices and load margin cost. Fig.1 illustrates some typical P-V curves for different operation situations; base case, just after contingency happens and after utilizing FACTS devices. The nose point of the P-V curve is called "*Point of voltage Collapse*" (PoC), where the voltage drops rapidly with an increase of load. PoC is also known as the equilibrium point, where the corresponding Jacobian matrix becomes singular. As shown in Fig.1, load margin is defined as the distance between the nose point and the base case operating point (A). After a contingency happens and installed FACTS devices are utilized, the system operating point moves to point (B). As shown in Fig.1, load margin in this case is less than base case, but the system is operating in stable zone.

The proposed objective function may be formulated as follows.

$$Minimize: F_{total} = \sum_{k=1}^{N} CRF * F_{Inst}^{k} + F_{lm}^{k} \tag{1}$$

Subject to:

1) Investment constraints (Upper and lower capacity limits of SVC devices)
2) Operation constraints (Load flow constraints)

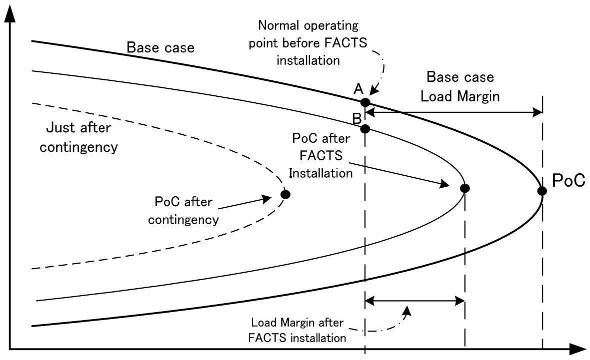

Figure 1. P-V curve showing the main concept of PoC and load margin

Where N is the number of contingencies and CRF is the Capital Recovery Factor and is calculated as (2) based on the values of interest rate (*ir*) and life period of VAr devices (*Dy*).

$$CRF = \frac{ir(1+ir)^{Dy}}{(1+ir)^{Dy}-1} \tag{2}$$

F_{Inst} is the investment cost of SVC devices where, Ω is the set of all candidate sites, C_{iSVC} is the capacity of the installed SVC *in KVAr*. μ_{iSVC} is the investment cost factor in \$/KVAr based on the data provided in [18].

$$F_{Inst} = \sum_{i \in \Omega} \mu_{iSVC} c_{iSVC} \tag{3}$$

$$\mu_{iSVC} = 0.0003\, c_{iSVC}^2 - 0.3051\, c_{iSVC} + 127.38 \tag{4}$$

The load margin cost (F_{lm}) is defined as (5) where, ρ is a penalty cost factor; lm_{Des} is desired load margin; lm_{Ins} is the load margin after SVC installation.

$$F_{lm} = \begin{cases} \rho(lm_{Des} - lm_{Ins}) & \text{if } lm_{Des} > lm_{Ins} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

III. MODERN HEURISTIC TECHNIQUES

A. Initialized Population

To expand the solution algorithm introduced in [3] for finding the optimal allocation of different types of FACTS devices, the expanded population structure of individuals is introduced and illustrated in Fig.2. Each individual (X_i) which is considered to be a solution for the problem includes the allocation data of different types of FACTS devices. The value of each cell is the capacity of the FACTS device which is scheduled to be installed. By this arrangement candidate buses for each device can be determined independently and problem can be solved for multi-type FACTS devices. The capacity of FACTS devices are considered as discrete numbers ranging over the lower and upper limits, which is assumed 0 and 0.3 in this work, respectively. It should be emphasized that by using this population structure, and considering the steady state model of FACTS devices in power flow calculations the proposed allocation problem can be straightforwardly applied to locate any type of FACTS devices.

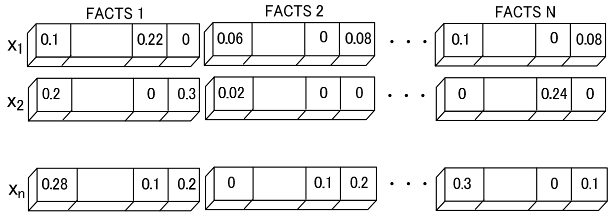

Figure 2. Expanded Structure of the population of individuals

B. Genetic Algorithms (GA)

Genetic Algorithms are global search techniques developed by Holland *et al.* [19], based on the mechanisms of natural selection and genetics and the principles of Darwinian evolution.

GA searches for the optimal solutions by sampling the search space at random and creating a population of candidate solutions. GA transforms a *population* of individual objects, each with an associated *fitness* value, into a new *generation* of the population using the Darwinian principle of reproduction and survival of the fittest and naturally occurring genetic operations such as *crossover* (*recombination*) and *mutation*. Each individual in the population represents a possible solution to a given problem [20].

In this paper a modified version of GA has been used in which integer representation is performed as shown in Fig. 2. Each chromosome of the population consists of two parts, containing the size and the place of the FACTS to be installed. Length of each chromosome is equal to the number of the candidate sites for the installation of all FACTS devices. At the initial step a random population based on the illustrated structure is generated. New generated chromosomes are checked to be within the specified limits and a truncation policy is done for the values according to the capacity constraints. If the value of any chromosome exceeds its limit, it will be given the limit value.

As for the GA operators, one-point crossover is used in this paper and the mutation is exactly the typical one except that the chosen random positions are changed from zero to a randomly selected value within the upper and lower limit and vice versa. Reproduction is implemented using biased roulette wheel method.

C. Particle Swarm Optimization (PSO)

PSO is a kind of evolutionary algorithm, which is basically developed through simulation of swarms such as flock of birds or fish schooling [10]. Similar to evolutionary algorithm, PSO conducts searches using a population of random generated particles, corresponding to individuals (agents). However in PSO, particles evolve in the search space motivated by three factors: *inertia, memory and cooperation*. *Inertia* implies a particle keeps moving in the direction it had previously moved. *Memory* factor influences the particle to remember the best position of the search space it has ever visited. *Cooperation* factor induces the particles to move closer to the best point in space found by all particles. Each particle is a candidate solution to the optimization problem which, has its own position and velocity represented as *x* and *v*.

Searching procedure by PSO can be described as follows: a flock of agents optimizes an objective function. Each agent knows its best value (*pbest*), while the best value in the group (*gbest*) is also known. New position and velocity of each agent is calculated using current position and best values *pbest* and *gbest* as below:

$$v_i^{k+1} = wv_i^k + c_1 r_1 \times (pbest - x_i^k) + c_2 r_2 (gbest - x_i^k) \quad (10)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (11)$$

Where, k is the number of current generation; w is called inertia weight; r_1 and r_2 are random numbers between 0 and 1; c_1 and c_2 are two positive constants, called cognitive and social parameter respectively. The computational flowchart of the developed PSO is shown in Fig. 3.

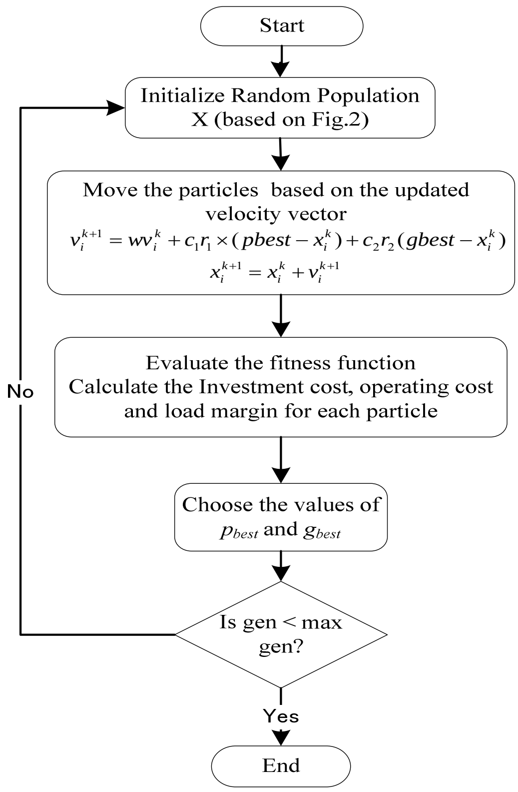

Figure 3. Computational flowchart of the developed PSO

The first term in (11) represents inertia, the second term represents memory and the third one stands for cooperation factor. Inertia weight was first introduced by Shi and Eberhart [21]. The inertia weight is used to control the impact of the previous velocities on the current velocity, influencing the trade-off between the global and local experience.

Although Zheng *et al.* [22] claimed that PSO with increasing inertia weight performs better, linear decreasing of the inertia weight is recommended by Shi and Eberhart [21, 23]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} iter \qquad (12)$$

Where w_{max} and w_{min} are maximum and minimum of inertia weight value respectively, $iter_{max}$ is maximum iteration number and *iter* is the current iteration. The authors claimed that the following parameters are appropriate and the values *do not depend* on the problems:

$w_{max}=0.9$, $w_{min}=0.4$, $c_1=c_2=2$

The values are also reported to be appropriate for power system problems [11, 3].

A so-called constriction factor *K*, is presented in [24]. It has been claimed that this factor increases the algorithm's ability to convergence to a good solution and can generate higher quality solution than the conventional PSO approach. In this case, the expression used to update the particle's velocity becomes:

$$v_i^{k+1} = K * (v_i^k + c_1 r_1 \times (pbest - x_i^k) + c_2 r_2 (gbest - x_i^k)) \qquad (13)$$

Where,

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \varphi = c_1 + c_2, \varphi > 4 \qquad (14)$$

D. Evolutionary Particle Swarm Optimization (EPSO)

EPSO was developed by Miranda *et al.* [16] that combines conventional PSO with the evolutionary strategy. EPSO puts together the concepts of Evolution Strategies (ES) and of PSO. The particles move according to the conventional PSO movement rule, but the strategic parameters are selected according to ES procedure. Therefore, it is expected that the exploratory power of PSO and self-adaptation power of ES is obtained.

EPSO starts the same as PSO, with a population of particles, generated randomly in the search space. Then, within the number of iterations, the following steps are implemented:

1) *Replication*: Each particle is replicated *r* times (usually *r* is considered 2*)*

2) *Mutation*: The weights of the replicated particles are mutated according to:

$$w_{ik}^* = w_{ik} + \tau N(0,1) \qquad (15)$$

Where τ is a learning parameter (either fixed or treated also as strategic parameters and therefore also subject to mutation), and N(0,1) is a random variable with Gaussian distribution, 0 mean and variance 1.

3) *Reproduction*: Each particle generates as offspring a new particle according to the movement rule by (16), similar to the equations (10) and (11) of conventional PSO. The replicated particles make use of the mutated weights. The offspring is held separately for the original particles and the mutated ones. The value of *gbest* is also mutated using a so called *learning parameter* (τ`).

$$v_i^{k+1} = w_{i0}^* v_i^k + w_{i1}^* \times (pbest - x_i^k) + w_{i2}^* (gbest^* - x_i^k) \qquad (16)$$

$$gbest^* = gbest + \tau' N(0,1) \qquad (17)$$

τ` is a learning parameter (either fixed or treated also as strategic parameters and therefore also subject to mutation).

4) *Evaluation:* Each particle is evaluated according to their current position.

5) *Selection*: The best particles are selected by stochastic tournament or other selection procedure, to form a new generation.

Figure 4 illustrates the outline of the proposed EPSO.

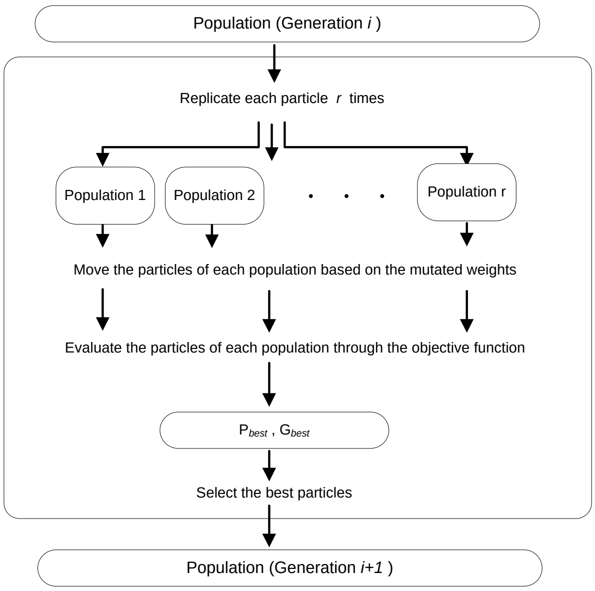

Figure 4. Outline of the developed EPSO algorithm

IV. NUMERICAL RESULTS

IEEE 14 and 57-bus test systems are used to demonstrate the application of the proposed formulation and evaluate the effectiveness of the modern heuristic techniques in solving the SVC allocation problem. Simulations were implemented using MATLAB 6.5 on a PC with an Intel Core 2 (2.4GHz) processor. Life period of VAR control devices (Dy) and the interest rate (ir) are assumed 10 years and 0.04 respectively. Desired load margin is assumed 0.2.

Table I shows the values of minimum voltages and load margins for just after different possible contingencies for IEEE 14-bus test system.

TABLE I.
LOAD MARGINS AND MINIMUM VOLTAGES FOR SEVER CONTINGENCIES

	Minimum Voltage	Load Margin
Cont 1. (Line 1-2)	0.604	-0.0374
Cont 2. (Line 1-5)	0.583	-0.0147
Cont 3. (Line 2-3)	0.605	0.0383
Cont 4. (Line 2-4)	0.574	0.0914
Cont 5. (Line 2-5)	0.572	0.1012
Cont 6. (Line 3-4)	0.573	0.01651
Cont 7. (Line 4-5)	0.572	0.1451
Cont 8. (Line 6-11)	0.570	0.1667

As it is shown in table I, for some contingencies the load margin is negative and system will be derived to unstable zones. In these cases, installation of FACTS devices to control the voltage and mitigate voltage instability is needed.

To find the optimal allocation of FACTS devices, the optimization problem is solved by the developed modern heuristic techniques. The number of population for all modern heuristic techniques in this paper is assumed 40 and maximum number of iterations ($iter_{max}$) is 100. Probabilities of mutation and crossover operators are 0.1 and 0.6, respectively. Learning parameter (τ) of EPSO is assumed 0.5.

Table II shows the optimal allocation of SVCs through the proposed modern heuristic techniques for IEEE 14 and 57 buses test systems. Values in table II present the place and amount of SVCs to be installed, for example 8(0.16) means that the capacity of the SVC to be installed in bus 8 is 0.16 pu.

TABLE II.
OPTIMAL ALLOCATION OF SVCS

Test system	Solution Method	Allocation of SVC
IEEE-14 buses	GA	8(0.3), 9(0.3), 10(0.28)
	PSO	8(0.3), 9(0.3), 11(0.26)
	EPSO	8(0.3), 9(0.3), 10(0.24)
IEEE-57 buses	GA	28(0.3), 30(0.3), 32(0.28)
	PSO	30(0.26), 31(0.3), 32(0.28)
	EPSO	31(0.2), 30(0.3), 32(0.28)

Fig.5 and Fig.6 illustrate the convergence graphs of GA, PSO and EPSO for IEEE-14 and 57 buses test systems, respectively. Population size and the maximum number of iterations in all techniques are the same.

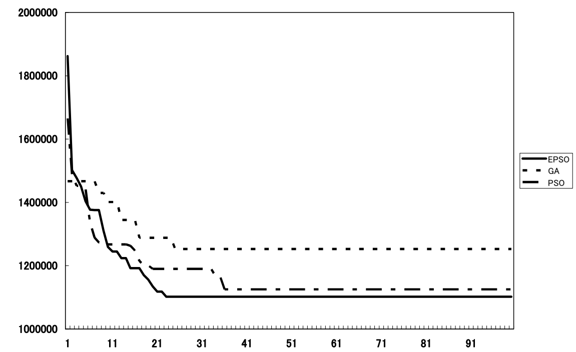

Figure 5. Convergence characteristics of GA,PSO and EPSO (IEEE-14 buses test system)

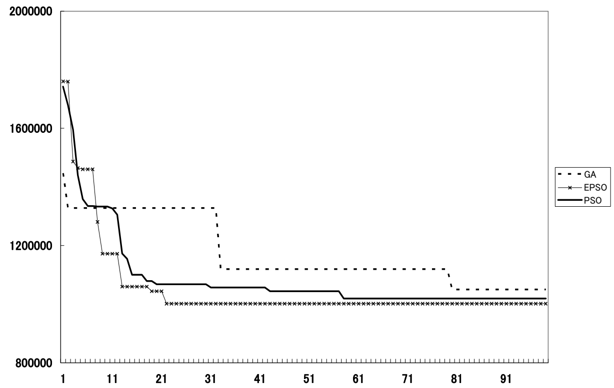

Figure 6. Convergence characteristics of GA,PSO and EPSO (IEEE- 57 buses test system)

To investigate the application feasibility of the proposed modern heuristic techniques in solving large scale optimization problems, the above mentioned techniques are also applied to the RPP problem formulation in [3]. In the proposed RPP problem, SVC and SC are utilized during corrective and preventive controls to keep the desired system security level. SVC as a fast control device is utilized during corrective control and SC as a slow control device is utilized during preventive control. Due to the low investment cost of SVC and SC compare to the cost of load shedding, in all obtained solutions load shedding is mitigated after utilization of FACTS devices and considerable cost saving is achieved.

Table III presents the minimum bus voltages and load margins for base case and just after contingency states in each load level. As shown in table III in the case of some contingencies load margin is negative and system will be derived to unstable zones. In these cases, corrective control has to be carried out to transfer the system to the stable zone and then preventive control should be initiated to maintain system security and obtain the desired load margin (desired load margin during corrective and preventive controls are assumed 0.05 and 0.2, respectively in this paper).

TABLE III.
MINIMUM BUS VOLTAGES AND LOAD MARGINS FOR BASE CASE AND JUST AFTER CONTINGENCY STATES

		Base Case	Cont.#1	Cont.#2	Cont.#3
Load Level 1	Min. Voltage	0.793	0.604	0.583	0.605
	Load Margin	0.171	-0.037	0.014	0.038
Load Level 2	Min. Voltage	0.760	0.574	0.572	0.573
	Load Margin	0.121	0.051	0.080	0.115
Load Level 3	Min. Voltage	0.744	0.572	0.570	0.570
	Load Margin	0.101	0.075	0.096	0.094

To demonstrate the cost effect of utilizing slow and fast devices during corrective and preventive controls, three scenarios have been analyzed. It has to be mentioned that load conditions and parameter settings for all scenarios are the same. To compare the effectiveness of the optimization methods, each scenario is simulated by GA, PSO and EPSO independently. In scenario 1, there are not any FACTS devices to be installed and load shedding is the only control device. SVC is the only FACTS device which is used to be installed during scenario 2 and finally both SC and SVC are used to be utilized in scenario 3. Table IV presents the cost effect of new VAR installation simulated by the heuristic methods. As expected, load shedding cost is reduced after new VAR installation. All the values in table IV are in US$.

TABLE IV.
MINIMUM BUS VOLTAGES AND LOAD MARGINS FOR BASE CASE AND JUST AFTER CONTINGENCY STATES

		Load shedding cost	SVC Inst. Cost	FSC Inst. Cost	Saving Cost
GA	Scenario 1	$2.45*10^8$	0	0	0
	Scenario 2	0	$8.83*10^7$	0	$1.56*10^8$
	Scenario 3	0	$6.95*10^7$	$1.82*10^7$	$1.57*10^8$
PSO	Scenario 1	$2.45*10^8$	0	0	0
	Scenario 2	0	$8.7*10^7$	0	$1.59*10^8$
	Scenario 3	0	$1.23*10^7$	$4.59*10^7$	$1.86*10^8$
EPSO	Scenario 1	$2.45*10^8$	0	0	0
	Scenario 2	0	$8.3*10^7$	0	$1.6*10^8$
	Scenario 3	0	$1.2*10^7$	$4.4*10^7$	$1.89*10^8$

Fig.7 depicts the convergence of the applied solution methods for the VAR planning problem. With the same population size and the maximum number of iterations, EPSO has better performance than PSO and also GA.

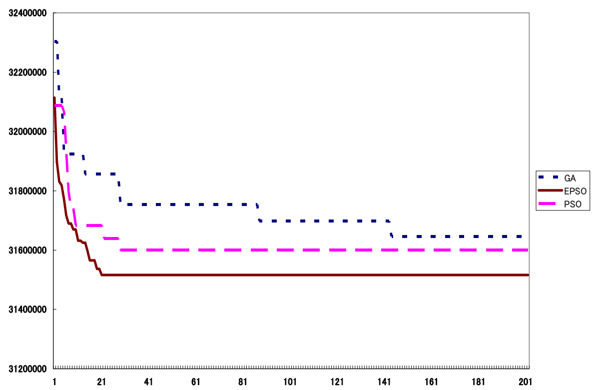

Figure 7. Convergence of the Solution methods

V. CONCLUSIONS

Three well-known modern heuristic techniques have been applied to solve the SVC placement problem and comparative study is conducted to illustrate the performances and effectiveness of the proposed techniques. Even though all the proposed techniques produced optimal or near optimal solution, required numbers of iterations to obtain the optimal solution through PSO and EPSO are less than GA. Moreover comparing the results obtained by GA, PSO and EPSO techniques depicts that PSO based techniques outperform others in terms of calculation time and not trapping into local minima. Proposed modern heuristic techniques have also been applied successfully to a large scale mixed-integer nonlinear programming reactive power planning problem. Numerical results depict that considerable cost saving can be achieved through optimal allocation and combination of VAr devices while maintaining the desired system security level.

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