Application of Evolutionary Multi Objective Optimization Algorithm to Optimal VAr Expansion and ATC Enhancement Problems

Mehdi Eghbal, Naoto Yorino and Yoshifumi Zoka
Hiroshima University
HigashiHiroshima, JAPAN

E.E.El-Araby
Suez Canal University
Port Said, EGYPT

***Abstract*— This paper presents Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to find the optimal solutions of VAr expansion problem considering the enhancement of Available Transmission Capacity (ATC). The aim is to obtain an optimal allocation of FACTS devices that is optimal in terms of minimizing the total cost and maximizing the amount of ATC. Violation of desired system security constraints is considered as a penalty cost which is calculated during normal and contingency states where corrective and preventive controls are utilized to mitigate voltage collapse and minimize the amount of load shedding. However, installation of FACTS devices is proved to improve ATC, on the other hand it increases the investment cost which conflicts with the objective function of the VAr expansion problem. MOPSO approach based on Pareto optimality is proposed to find a set of possible optimal solutions. The proposed approach has been successfully tested on IEEE 14 bus test system.**

***Index Terms*— Available Transmission Capacity, Multi Objective Particle Swarm Optimization, VAr Expansion, Voltage security**

I. Introduction

Optimal reactive power (VAr) expansion problem involves allocation and determination of the types and sizes of the new installed reactive supplies in order to optimize an objective function while satisfying system operation constraints. This problem has been solved using optimization methods and algorithms with different objective functions. The main presented objective functions are system loadability maximization [1], overall operation cost minimization [2], congestion management [3] and others. Zhang et al., in [4] reviewed various objectives, constraints and algorithms of reactive power planning problem. Most of the mentioned works do not consider voltage security constraints and system operation and investment costs in an integrated formulation. An integrated voltage security reactive power planning considering investment costs is presented in the previous work of the authors in [5]. The proposed problem is formulated as a large-scale mixed integer nonlinear programming which has been solved by well-known heuristic methods.

The main objective of the proposed optimal VAr expansion problem is to minimize total cost, while satisfying desired system security constraints during normal and contingency states. Total cost includes installation costs of new VAr devices and operation costs. To maintain desired system security level, corrective and preventive controls are utilized to mitigate voltage collapse and load shedding. To minimize the investment cost, a combination of cheap and expensive devices concerning their performances is proposed. Fast devices which are expensive are used during corrective control to quickly return the system back to stable operation point. Then, other slow devices which are cheaper are utilized during preventive control. Details of the experiments on this problem can be found in [5].

Meanwhile, installation of FACTS devices is proved to improve Available Transmission Capacity (ATC). ATC is defined as a measure of the transfer capability in the physical transmission network for transfers for future commercial activities over already committed uses [6]. As a result, power suppliers will benefit from more market opportunities with less congestion and enhanced power system security. In other hands, because of tight restrictions on the constructions of new facilities due to economic, environmental and social problems, it is important to ascertain the optimal allocation of new installed VAr devices. Recently, various heuristic methods have been adopted to enhance ATC by installing optimum number of FACTS devices [7-8].

Several methods for optimal allocation of VAr devices to minimize total cost and maximize ATC has been proposed but to the best knowledge of the authors, an integrated approach to find simultaneously the optimal solution considering both objective functions has not been reported. To do so, the single objective VAr planning problem introduced in [5], is upgraded and enhanced to a multi objective optimization problem. Total cost of the optimal VAr allocation and the amount of ATC are defined as the objective functions in this paper.

Optimizing several objective functions simultaneously which are sometimes even non-commensurable and conflicting with each other, is done by multi objective optimization methods. These methods are able to find multiple optimal solutions rather than only one local optimal solution. To solve multi-objective optimization problems, several methods have been proposed. They are mainly categorized as classical and evolutionary methods [9].

It can be seen that recently evolutionary multi-objective optimization methods have been used in solving power system problems due to their nice feature of population based search [10]. In this paper a MOPSO algorithm is used which allows the conventional PSO algorithm to be able to deal with multiple objective functions. It has been reported that the

MOPSO algorithm outperforms other evolutionary multi-objective optimization methods [11].

The paper is organized as follows. Section 2 introduces the main concepts of multi-objective optimization. Problem formulation is the subject of Section 3, which itself is divided into three parts: describing the VAr expansion problem, ATC problem and the solution method for the overall problem. Section 4 is devoted to simulation results and illustrates the simulation results on IEEE 14 bus system. The last section offers concluding remarks and future perspectives.

II. Multi-Objective Optimization

Many real world problems involve simultaneous optimization of several objective functions. Generally, these objective functions are non-commensurable and often conflicting. Solving such conflicting objective functions give rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as *Pareto-optimal* solutions. A set of Pareto solutions is called *Pareto set* and its image on the objective space is called *Pareto-front* [9].

To solve multi-objective optimization problems, several methods have been proposed. They are mainly categorized as classical and evolutionary methods. Classical methods have been around for last four decades. A list of a few commonly used classical multi-objective optimization methods can be found in [9]. Evolutionary algorithms mimic natural evolutionary principles to constitute search and optimization process. Comparing these two methods indicate that evolutionary methods outperform classical methods in many aspects.

GA, Strength Pareto Evolutionary Algorithm and Multi-objective PSO (MOPSO) are main multi-objective evolutionary optimization methods. A comparison of several multi-objective evolutionary optimization methods is addressed in [12].

In this paper, MOPSO is used to solve the proposed optimization problem and explained in the following section.

A. Multi-objective PSO

PSO is a kind of evolutionary algorithm, which is basically developed through simulation of swarms such as flock of birds or fish schooling [13]. Similar to evolutionary algorithm, PSO conducts searches using a population of random generated particles, corresponding to individuals (agents). An important difference between PSO and evolutionary algorithm is the fact that PSO allows individuals to benefit from their past experiences whereas in an evolutionary algorithm, normally the current population is the only "memory" used by the individuals. 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 (p_j^i), while the best value in the group ($p_j^{i,g}$) is also known. New position and velocity of each agent is calculated using current position and best values p_j^i and $p_j^{i,g}$ as below:

$$v_j^{i+1} = wv_j^i + c_1 r_1 \times (p_j^i - x_j^i) + c_2 r_2 (p_j^{i,g} - x_j^i) \quad (1)$$

$$x_j^{i+1} = x_j^i + v_j^{i+1} \quad (2)$$

Where, w is called inertia weight; r_1 and r_2 are random numbers between 0 and 1; c_1 and c_2 are called cognitive and social parameter respectively and are two positive constants between 1 and 2.

In the Multi Objective PSO, a set of non-dominated solutions must replace the single global best individual in the standard single objective PSO case. In addition there may be no single local best individual for each particle of the swarm. Choosing the global and local best to guide the swarm particles becomes nontrivial task in multi-objective domain. There exist several MOPSO methods which suggest different approaches to find the best guides for each particle in the swarm. Among these methods, it has been reported that sigma method has a good feature in finding solution for two objective functions [11]. Therefore, in this paper, MOPSO by sigma method is used.

B. Sigma method

This method was proposed by Mostaghim and Teich to find the best local guide for each particle [11]. In this method, first a value σ_i is assigned to each point with the coordinates of ($f_{1,i}$,$f_{2,i}$) in which all the points on the line $f_2=af_1$ have the same value of σ_i. σ_i is defined as follows:

$$\sigma_i = \frac{f_1^2 - f_2^2}{f_1^2 + f_2^2} \quad (3)$$

Therefore, all the points on the line $f_2=af_1$ have the same values as $\sigma_i =(1-a)/(1+a)$.

For the problem with m objective function, σ is a vector of elements in which each element of σ is the combination of two coordinates in terms of (3) as below:

$$\sigma = \begin{pmatrix} f_1^2 - f_2^2 \\ f_2^2 - f_3^2 \\ \vdots \end{pmatrix} / \left(f_1^2 + f_2^2 + f_3^2 \cdots \right) \quad (4)$$

Using the basic idea of Sigma method and by considering the objective space, finding the best local guide ($p_j^{i,g}$) among the archive members for the particle j of the population is as follows: in the first step, the value σ_k is assigned to each particle k in the archive. In the second step, σ_j for the particle j of the population is calculated. For each particle j, the archive member k which its σ_k has the minimum distance to σ_j is selected as the best local guide for particle j during iteration i ($p_j^{i,g} = x_k$). In the case of two-dimensional objective space, difference between the sigma values of two particles indicates the distance between them; in the case of m-dimensional objective space, the *m*-Euclidian distance between the sigma values is considered as the distance between the particles. Figure 1 shows how the best local guide can be found among the archive members for each particle of the population for a two dimensional objective space.

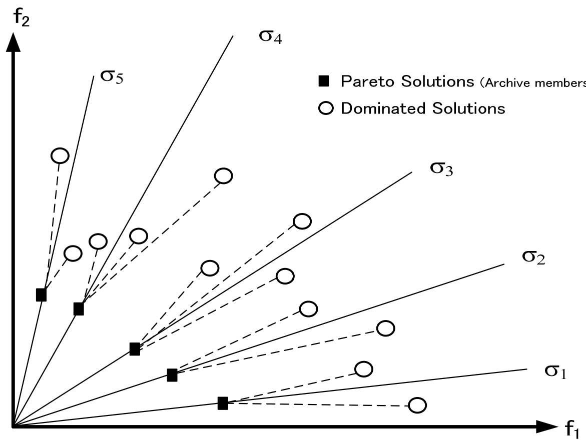

Figure 1: Finding the best local guide for each particle of the population using the Sigma method

When two σ values are close to each other, it means that the two particles are on two lines which are close to each other.

III. PROBLEM FORMULATION

A. Reactive Power (VAR) Expansion Problem

In general, VAr planning problem aims to optimize a specific objective function while considering variety of operating constraints. In this paper, minimizing total cost while satisfying desired system security constraints during normal and contingency states is considered as the main objective function of the VAr expansion problem. Total cost includes investment costs of new installed VAr devices, operation costs and system control costs. The cost effect of new installed VAr devices is evaluated in each possible state in power system transitions during base case and when contingencies happen.

It is assumed that the system is in normal operation state with minimum operation cost and desired security levels. After contingency *k* happens with probability α, corrective and preventive controls are utilized to return the system back to the desired secure operation point. Fast and slow VAr devices are being utilized in corrective and preventive states. SVC (Static VAr Compensator) and SC (Series Compensator) are considered as fast and slow devices, respectively. Load shedding is also considered as an expensive fast control during corrective control state.

The concept of Preventive/Corrective Control is illustrated in Fig.2. If the contingency *k* causes negative load margin, the fast devices in corrective state react to move the system into a voltage-secure operating point; moving from point $\overline{B}^{(k)}$ to $C^{(k)}$ in Fig.2. Controls in this state consist of fast control devices and load shedding which are expensive. After the fast corrective control, voltages may be violated and load margins are too small, and then the preventive control is activated to obtain adequate load margin i.e. moving from point $C^{(k)}$ to $D^{(k)}$. Slow devices, as well as fast devices, can be utilized during preventive control in this state. Therefore, reliability of the system operation is guaranteed after corrective and preventive control.

In this paper, we will compute optimal VAr allocation for the slow and fast devices so that the system will transfer directly from base case to corrective control state very quickly and from corrective control state to preventive control state smoothly to keep pre-specified load power margins for corrective and preventive states.

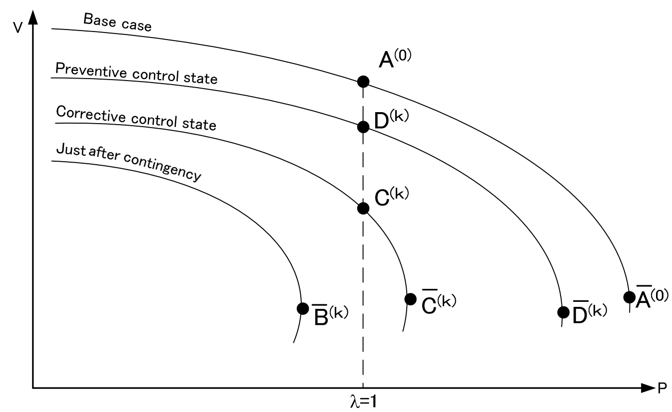

Figure 2: PV Diagrams for Corrective/Preventive states

Main objective function which is the total cost may be formulated as (5). It is the sum of total investment cost and total operating cost. The total operating cost is the summation of operating costs which consist of expected costs of base case and control states during normal and contingency situations, respectively.

$$Minimize: F_{total} = F_{It} + F_{op} \tag{5}$$

Subject to:

1) Investment constraints $0 \le C_{iSVC}, C_{iSC} \le C_{It,\max}$

2) Operation constraints (load flow constraints)

C_{isvc} and C_{isc} are the capacity of the installed SVC and SC in bus *i in KVAr* and $C_{It,max}$ is maximum VAr compensation of SVC and SC.

F_{It} is the annual value of the total investment cost of slow and fast devices which is calculated based on data provided in [14] and the capital recovery factor as (6).

$$F_{It} = \frac{ir(1+ir)^{Dy}}{(1+ir)^{Dy}-1} * \sum_{i\in\Omega} \left(\mu_{iSVC} C_{iSVC} + \mu_{iSC} C_{iSC}\right) \tag{6}$$

In the above equation *ir* and *Dy* are interest rate and life period of VAr devices, respectively. *Ω* is the set of all candidate sites, μ_{isvc} and μ_{isci} are the investment costs of SVC and SC in *\$/KVAr.*

The second term in (5) is the operating and control cost which includes the costs during base case, corrective and preventive control states taking into account the probability of contingencies and is formulated as (7).

$$F_{op} = \left(1 - \sum_{k=1}^{n} \alpha^{(k)}\right) F_A + \sum_{k=1}^{n} \alpha^{(k)} \left(F_C^{(k)} + F_D^{(k)}\right) \quad (7)$$

In which, $\alpha^{(k)}$ is the probability of contingency k. F_A is base case operating cost, $F_C^{(k)}$ and $F_D^{(k)}$ are corrective and preventive control costs for contingency k, respectively. The cost functions of the corrective and preventive controls after each contingency include the cost of load shedding, control cost for reactive powers and the cost of voltage collapse and are formulated as follows.

$$F_C^{(k)} = \sum_{l=1}^{N_s} \mu_{s,l} \left|S_{c,l}^{(k)}\right| + \sum_{j=1}^{N_c} \mu_{C,j} \left|c_{C,j}^{(k)} - c_{A,j}\right| + \sum_{i=1}^{Np} \mu_{p,i} \left|p_{C,i}^{(k)} - p_{A,i}\right| \quad (8)$$

$$F_D^{(k)} = \sum_{l=1}^{N_s} \mu_{s,l} \left|S_{c,l}^{(k)}\right| + \sum_{j=1}^{N_c} \mu_{D,j} \left|c_{D,j}^{(k)} - c_{C,j}^{(k)}\right| + \sum_{i=1}^{Np} \mu_{p,i} \left|p_{D,i}^{(k)} - p_{A,i}\right| \quad (9)$$

Where,

$S_{c,l}$	amount of load shedding
$\mu_{s,l}$	cost for unit load curtailment.
$\mu_{C,j}$	control cost coefficient for fast device j
$\mu_{D,j}$	control cost coefficient for slow device j
$\mu_{p,i}$	control cost coefficient for VAr controls
c	control parameter vector of VAr devices
p	control parameter vector excluding VAr devices

In equations (8) and (9), the indexes A, C and D stand for base case, corrective and preventive control states, respectively. The objective functions of corrective and preventive states are to minimize the total control cost considering the probability of the contingency k ($\alpha^{(k)}$) and are formulated as (10) and (12) subject to operating constraints (11) and (13), respectively.

$$\text{Minimize} \sum_{k=1}^{n} \alpha^{(k)} F_C^{(k)} \quad (10)$$

subject to:

$$\begin{cases} G_C^{(k)} \le 0 & \text{Nominal load operating point constraint} \\ \overline{G}_C^{(k)} \le 0 & \text{Voltage collapse point constraint} \end{cases} \quad (11)$$

$$\text{Minimize} \sum_{k=1}^{n} \alpha^{(k)} F_D^{(k)} \quad (12)$$

subject to:

$$\begin{cases} G_D^{(k)} \le 0 & \text{Nominal load operating point constraint} \\ \overline{G}_D^{(k)} \le 0 & \text{Voltage collapse point constraint} \end{cases} \quad (13)$$

Optimal operating points in base case, corrective and preventive states are obtained by a Successive Linear Programming (SLP) optimization algorithm. Objective function of each sub-optimization problem is minimization of operating costs considering system security constraints which, details are explained in [5].

B. *Available Transmission Capacity (ATC)*

The basic idea in the ATC calculation is to determine the maximum amount of power that a transmission system can transport, in addition to the already committed transmission services without the violation of transmission constraints for a given set of system conditions [6]. Based on the ATC definition, it can be formulated as an optimization problem in (14) to maximize the value of λ.

$$\begin{aligned} &\text{Maximize } \lambda \\ &\text{Subject to } \; f(x,\lambda) = y_0(x) + \lambda y_d - g(x) = 0 \end{aligned} \quad (14)$$

$$\begin{aligned} &\underline{v_i^2} \le v_i^2 \le \overline{v_i^2} && i = 1,\cdots,n \\ &\underline{Q_{Ri}} \le Q_{Ri} \le \overline{Q_{Ri}} && i \in S_R \\ &\underline{P_{Gi}} \le P_{Gi} \le \overline{P_{Gi}} && i \in S_G \\ &\underline{P_{ij}} \le P_{ij} \le \overline{P_{ij}} && i = 1,\cdots,n;\, j = 1,\cdots,n, i \ne j \end{aligned} \quad (15)$$

Where:

λ	scalar parameter representing loading level
$x = [P_G; Q_R; v]^T$	all state variables vectors
$P_G = [P_{G1},\cdots, P_{Gn}]^T$	active power vector in each node
$Q_R = [Q_{R1},\cdots, Q_{Rn}]^T$	reactive power vector in each node
$v = [v_1, \cdots, v_n]^T$	bus voltage vector
i, j	node number
n	total number of all nodes
$f(x,\lambda)$	extended load flow equation
$y_0(x)$	node injected power vector
$g(x)$	power flow equation
$\overline{*}, \underline{*}$	upper and lower limit value
S_R	set of reactive power sources
S_G	set of active power sources
y_{dP}, y_{dQ}	specified change in active, reactive power injection
$y_d = [y_{dP}; y_{dQ}]^T$	change direction vector of node injected power

The ATC between two areas or two points can be calculated, by appropriate specification of $\boldsymbol{y}_d$ according to the above mentioned formulation.

C. *Overall problem*

The overall problem is formulated as a nonlinear constrained multi objective optimization problem with two objective functions. Total cost of optimal VAr expansion problem and ATC enhancement are the objective functions. So the overall problem would be a min-max optimization problem.

Since the Sigma method can only work on the positive values of the objective space, all the test functions must have positive values. Therefore, in this paper without loss of generality it is assumed that $f_2 = K - ATC$ where, K is a positive constant parameter. Assuming this, the overall problem would be a min-min optimization problem which is solved by a MOPSO algorithm. Fig.3 shows main algorithm of the proposed MOPSO method.

Begin
INPUT: Initial parameters (system and load data)
OUTPUT: Pareto optimal solutions
Step1: t=0
Step2: Initialize random population X^t
Step3: Initialize $v=0; p^t=X, A^t=[]$
Step4: A^{t+1}=**Update** (P^t, A^t)
Step5: $P^{t,g}$=**Find_global_best** (A^t, X^t)
Step6: $v^{t+1}=wv^t+c_1r_1(p^t-X^t)+c_2r_2(p^{t,g}-X^t)$; $X^{t+1}=X^t+v^{t+1}$
Step7: **Evaluate** (X^{t+1})
Step8: P^t=**Find_local_best** (A^t, X^t)
Step9: Unless a stopping criterion is met $t=t+1$ and goto step4
End

Figure 3: Main algorithm of the proposed MOPSO method

In figure 3, function *Evaluate*, evaluates the particles in the population X^t, which it means calculating the objective functions for each particle. Function *Update*, updates the archive members by removing the dominated members and keeping the non-dominated ones. Selecting the global best partcile ($p_t^{i,g}$) for each partcile is done in *Find_global_best function* using Sigma method. Based on dominancy concept, the local best particle (p_t^i) for each particle is updated by the function *Find_local_best* in each iteration. p_t^i is like a memory for the particle i and keeps the non-dominated (best) position of the particle i. If neither p_t^i nor particle i dominates each other, local best particle can be either of them, which is usually selected by random.

IV. SIMULATION RESULTS

To validate the efficiency of the proposed algorithm, it has been examined on IEEE-14 bust system. In VAr expansion problem, the base case is defined by stressing the system to 158% of the original load. The parameters used for the system are given in [5]. The life period of VAR control devices (*Dy*) and the interest rate (*ir*) are assumed to be 10 years and 0.04, respectively.

Although all the contingencies can be considered, to reduce the calculation time only the three severest contingencies have been considered. In this simulation, contingency is considered as the outage of single line of a double parallel line. The capacities of slow and fast devices are assumed discrete numbers between 0 and 0.3 in which the step size is 0.02. Each particle which is a solution for the optimization problem is the place and size of installed VAr devices. In these simulations, the constant parameter K is assumed 1.5 which means the value of ATC is equal to $1.5\text{-}f_2$.

The parameters of the PSO are assumed as $w=0.1$, $c_1=c_2=2$, $itermax=200$, in which *itermax* is the maximum number of iterations. Population size is considered 30. The values of the PSO parameters are selected based on some trial and error. Proper parameter initialization leads to better convergence and variety in optimal Pareto front solutions.

Table 1 shows the minimum bus voltages and load margins for three contingencies before and after VAr expansion. It can be seen that before VAr expansion for the first contingency, load margin becomes negative which results in voltage collapse. After VAr expansion due to sufficient VAr sources installation minimum desired load margin is obtained.

	Before VAr Expansion		After VAr Expansion	
	Minimum Voltage	Load Margin	Minimum Voltage	Load Margin
Cont.1	0.604	-0.037	0.952	0.2
Cont.2	0.583	0.014	0.946	0.23
Cont.3	0.605	0.038	0.956	0.2

Table 1: Minimum bus voltages and load margin for different operation conditions.

Table 2 shows the value of ATC and total cost before and after VAr expansion. Operating condition for all patterns are the same. Each solution is an installation pattern in which the number inside () indicates capacity of the installed device in the candidate bus. For example 9(0.02) means that a 0.02pu VAr device is installed at bus number 9. The value of ATC is in pu and indicates the amount of ATC from bus 2 to bus 12 for all installation patterns. Total cost in table 2 is in 10^4\$ for all patterns which includes installation and operations costs. Pattern 1 is before VAr expansion and patterns 2 to 5 are typical obtained optimal solutions. Comparing the amount of ATC and total cost for pattern 1 and the others, indicates that optimal VAr expansion results in considerable cost saving and also ATC enhancement.

Pattern Code	SVC	SC	ATC	Total Cost
1	0	0	0.489	655.1
2	12(0.28),13(0.1)	11(0.08),14(0.28)	0.797	119.9
3	12(0.28),13(0.21)	11(0.2),14(0.28)	0.884	131
4	12(0.28),14(0.23)	11(0.26),13(0.28)	0.911	148.9
5	12(0.3),14(0.26)	11(0.3),13(0.3)	0.946	157.6

Table 2: Pareto optimal VAr expansion patterns.

As shown in table 2, when the value of ATC increases, the total cost also increases. Here, the main objective is to minimize total cost and maximize ATC. To ease the decision making process, a set of optimal solutions rather than only one solution is presented. The best compromise solution among the Pareto fronts can be selected by the system planner based or Fuzzy rules. Figure 4 illustrates the Pareto optimal front for the optimization problem after 200 iterations.

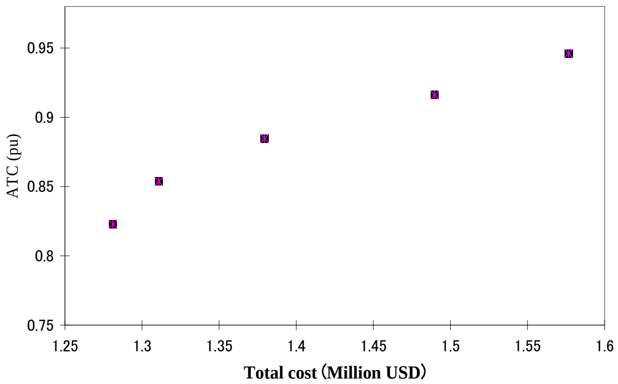

Figure 4: Pareto optimal solutions after 200 iterations.

V. CONCLUSIONS

In this paper, reactive power expansion problem is treated as a multi objective optimization problem with two conflicting objective functions: (1) total cost including investment and operation costs, (2) amount of ATC. A Multi Objective Particle Swarm Optimization approach has been introduced in which candidate solutions are the size and place of new installed VAr devices. Solutions of the optimization problem enhance the amount of ATC, reduce installation and operation costs, and mitigate any system security constraints violation under normal and contingency states.

The proposed approach has been successfully tested on IEEE 14 bus test system. The results indicate that the proposed approach is efficient for solving the proposed multi objective optimization problem where multiple Pareto optimal solutions can be found in one simulation run. As future work, clustering techniques are being developed to improve the diversity and distribution of the solutions and application of other heuristic techniques to solve the problem is under investigation.

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BIOGRAPHIES

Mehdi Eghbal received B.S. degree in Electrical Engineering from Ferdowsi University of Mashhad, Iran in 1998, M.S. degree in 2001 from Tarbiat Modares University, Tehran, Iran. He is currently preparing for a PhD in the area of application of heuristic techniques to power system at the Department of Artificial Complex Systems Engineering, Hiroshima University. He was with Tavanir Organization, Iran from 2000 to 2002. His research interest lies in power system planning and optimization.

Naoto Yorino received B.S., M.S. and Ph.D degrees in Electrical Engineering from Waseda University, Japan, in 1981, 1983, and 1987, respectively. He is a Professor in Graduate school of Engineering, Hiroshima University, Japan. He was with Fuji Electric Co., Ltd., Japan from 1983 to 1984. He was a Visiting Professor at McGill University, Montreal, QC, Canada, from 1991 to 1992. His research interests are power system planning, stability and control problems. Dr. Yorino is a member of the IEE of Japan and SICE

Yoshifumi Zoka received B.S. degree in Electrical Engineering, M.S. and Ph.D. degrees from Hiroshima University, Japan. He is currently an Associate Professor in Graduate school of Engineering, Hiroshima University. He was a research associate at University of Washington, Seattle, WA, USA from 2002 to 2003. His research interest lies in power system planning, stability and control problems. Dr. Zoka is a member of the IEE of Japan.

E.E.El-Araby received B.S. and M.S. degrees from Suez Canal University, Egypt, and the Ph.D. degree from the Department of Artificial Complex Engineering, Hiroshima University, Japan in 1990, 1996 and 2003 respectively. Presently he is an Assistant Professor in the Department of Electrical Engineering at Suez Canal University, Port Said, Egypt. He was a postdoctoral fellow at Department of Artificial Complex Engineering, Hiroshima University, Japan from 2004 to 2006. His research interests are power system planning, operation and ancillary services pricing in electricity markets.