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Optimal Location of SVC for Voltage Security Enhancement using MOPSO

Abdelaziz Laïfa and Mohamed Boudour

***Abstract*— Location of the static VAR compensator (SVC) and other types of Flexible AC Transmission Systems (FACTS) devices is important for the enhancement of practical power systems voltage stability. In this paper, a Multi-Objective Particle Swarm Optimization (MOPSO) is used to solve a mixed continuous-discrete multi-objective optimization problem in order to find optimal location of SVC. Simulations are performed on IEEE 14 test system for optimal location and size of SVC device. A contingency analysis to determine the critical outages with respect to voltage security is also examined in order to evaluate their effect on the location analysis. The obtained results show that with the allocation of SVC device with the proposed method, the voltage stability is considerably enhanced in both normal state and critical contingencies. The calculation of the load margin demonstrates the effectiveness of the proposed method.**

***Index Terms*— Voltage Stability, Voltage Collapse, Contingency Analysis, Voltage Security, SVC location, MOPSO.**

I. Introduction

For many years, voltage collapse problems in power systems have been of permanent concern for electric utilities and a subject of great importance due to the events of voltage instability and collapses that have occurred worldwide [1]. Voltage collapse is due to voltage instability. The later refers to the inability of a power system to maintain steady state voltages at all buses following a disturbance. However, voltage collapse is defined as the process by which the sequence of events accompanying voltage instability leads to a blackout or abnormally low voltages in a significant part of the power system [2]. Voltage collapse typically occurs on power systems that are heavily loaded, faulted and/or have reactive power shortage [2, 3]. Therefore, the voltage collapse problem is closely related to a reactive-power planning problem including contingency analyses, where suitable conditions of reactive-power reserves are necessary for secure operations of power systems [4]. The voltage collapse points are also known as maximum loadability points [1]. The loadability margin of a system is defined as the amount of power that the system can supply before it undergoes voltage collapse [3].

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Then, the system is said to be voltage secure, if the system has sufficient loading margin even after a credible contingency has occurred. Commonly, power systems are planned and operated based on the N-1 security criterion, which implies that the system should be able to remain in a security condition under all important first contingencies.

On the other hand, Flexible AC Transmission System (FACTS) devices, which can provide direct and flexible control of power transfer, can be very helpful in the operation of power networks. Both the power system performance and the power system stability can be enhanced by utilizing FACTS devices [5]. Consequently, such kinds of devices are able to improve power system security under contingency situations. However, the focus of this paper is on the placement of SVC, for enhancement of the stability margin and improving the voltage profile. SVC as a shunt compensation component is designed for voltage maintenance in power systems. It makes it possible the functioning of the system by increasing its loading margin. Thus, they are increasingly used in nowadays stressed transmission systems [6, 7].

For practical power systems, different buses are differently sensitive to the overall power system voltage stability. Some buses are more, and some are less. To a large extent, proper allocation of SVC can make great enhancement to voltage stability [5]. Therefore, it is an actual and important subject to appropriately select the suitable place for the FACTS device installation at the viewpoint of voltage security enhancement. This problem has retained the interest of worldwide researchers in power systems. Then, various methods and criteria were proposed and used to optimal allocation of FACTS devices in power systems [8-12].

The fact that optimization techniques can be readily used to study the voltage stability problem has led to formulations that "optimize" a system considering both economic and technical criteria. In this paper, an optimization approach is used where all the load buses are considered candidates for SVC installation. The problem is formulated as a nonlinear constrained multi-objective optimization problem where voltage deviations, voltage collapse impact and power losses are treated as competitive objectives in order to determine the optimal location of SVC. Several methods for locating optimal solutions, expressed from a multi-objective optimization perspective, have been developed in the way to solve power systems related problems. The multi-objective optimization approach has been the subject of many power system problems, and approached with different methods [13]. The use and development of heuristics-based multi-objective optimization techniques have significantly grown. Since they

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use a population of solutions in their search, multiple Pareto-optimal solutions can be found in one single run. These models can be efficiently used to eliminate most of the difficulties of classical methods [13]. As a consequence, various heuristic approaches have been adopted by researches including genetic algorithm, evolutionary programming and particle swarm optimization to evaluate and enhance network operation. Multi-Objective PSO is one of the new optimizers that have been investigated to achieve this task.

The remaining of this paper is organized as follows: section II presents a brief overview of multi-objective optimization problems. In section III, the PSO technique and the MOPSO algorithm are presented along with a detailed discussion. The problem formulation and the analysis methodology are presented in section IV. Finally, simulation results and contributions are discussed in section V. Conclusions are summarized in section VI.

II. MULTIOBJECTIVE OPTIMIZATION

Many real-world problems involve simultaneous optimization of several objective functions. Generally, these functions are non-commensurable and often conflicting objectives. Multi-objective optimization with such conflicting objective functions gives 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 [13].

A general multi-objective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows [13]:

$$\text{Minimize} f_i(x),\ i = 1,...,N_{obj} \tag{1}$$

$$\text{Subject to constraints: } \begin{cases} g_j(x) = 0 & j = 1,...,M \\ h_k(x) \le 0 & k = 1,...K \end{cases} \tag{2}$$

The objective functions are conflicting one another and the aim is optimizing them simultaneously (without loss of generality it is assumed that the objectives are to be minimized). The decision vector x belongs to the feasible region (for decision vector x). f_i is the ith objective function; x is the decision vector representing a solution, and N_{obj} is the number of objectives. To compare candidate solutions in multi-objective optimization problems, the concept of Pareto dominance is used. A decision vector u is said to dominate another vector v (denoted $u \prec v$) if:

$$f_i(u) \le f_i(v) \wedge \exists i \in \{1,2,...,N\} : f_i(u) < f_i(v) \tag{3}$$

This means that the decision vector u is not worse than v in all objectives and is strictly better than v in at least one objective. In this case, the solution u dominates v; u is called the non-dominated solution. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set or the Pareto-optimal front.

III. PARTICLE SWARM OPTIMIZATION

A. PSO

Particle Swarm Optimization (PSO), which has gained rapid popularity as an efficient optimization technique, is relatively a recent heuristic introduced by Eberhart and Kennedy [14]. It is based on the analogy of swarm of birds and school of fish. In PSO, each individual called particle makes his decision using his own experience together with other individuals' experience. PSO has a flexible and well-balanced mechanism to enhance and adapt the global and local exploration and exploitation abilities within a short calculation time. The main advantages of PSO algorithm are summarized as: simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques [15]. However, these superior characteristics make PSO a highly viable candidate to be used for solving multi-objective optimization problems. In PSO, two different definitions are used: the individual best and the global best. As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained previously. The best position that is associated with the best fitness encountered so far is called the individual best or pbest. The global best, or gbest, is the best position among all of the individual's best positions achieved so far. Using the gbest and the pbest, the ith particle velocity is updated according to the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \tag{4}$$

Based on the updated velocities, each particle changes its position according to the equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{5}$$

where, w is a weighting function, c_j are acceleration factors and rand is a random number between 0 and 1,

The following weighting function is usually utilized [16-17]:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{6}$$

where w_{max} is initial weight, w_{min} the final weight, $iter_{max}$ is the maximum iteration number, and iter is the current iteration number.

B. MOPSO

PSO can not be immediately applied to multi-objective optimization problems, because there are essential distinctions between multiple and single objective optimization problems. First, the former is the set of one group or several groups of solutions, while the latter is only single solution or a group of series of solutions. In PSO, the information is sent out by the best particle which is followed by other individuals to quickly converge to a point. Therefore, it may easily cause the swarms to converge to the local area of Pareto front if the PSO is applied directly to multi-objective optimization problems.

In fact, there have been several proposals to extend PSO to handle multi-objectives: Dynamic neighborhood PSO proposed by Hu and Eberhart [17], the swarm metaphor of Ray and Liew [18], the Multi-Objective PSO (MOPSO) by

Coello and Lechuga [19], the approach of Fieldsend and Singh [20], the algorithm of Mostaghim and Teich [21], The Non-dominated Sorting PSO (NSPSO) of Li [22]. Since finding the best local guides for each particle in the swarm is important in MOPSO, in each of these methods different suggestions are given. In this paper, we use one of them which seems to have good features in finding solutions, the σ-MOPSO.

This method was proposed by Mostaghim and Teich [21] to find the best local guide for each particle. First a value σ_i is assigned to each point with the coordinates of (f_{1i} , f_{2i}) in which all the points on the line $f_2 = af_1$ have the same value of σ, where σ is defined as follows:

$$\sigma = \frac{f_1^2 - f_2^2}{f_1^2 + f_2^2} \tag{7}$$

Therefore, all the points on the line $f_2 = af_1$ have the same σ values as $\sigma_i = (1-a^2)/(1+a^2)$.

It should be noted that $\sigma = 0$ if $f_{1i} = f_{2i}$. When $f_{2i} = 0$ then $\sigma = 1$ and for $f_{1i} = 0$ then $\sigma = -1$. Also when $a > 1$ then σ is negative and then when $a < 1$ then σ is positive.

Finding the best local guide among the archived members for each particle of the population is done in a way that each particle which has a closer sigma value to the sigma value of the archived member, must select that archived member as the best local guide.

IV. Methodology For Optimal Location

As we already mentioned, this paper focuses on the optimal location and design of SVC. The SVC is defined as a shunt connected static Var generator or consumer whose output is adjusted to exchange capacitive or inductive so as to maintain or control specific parameters of electrical power system, typically a bus voltage [3]. It combines a series capacitor bank shunted by thyristor controlled reactor. Then, the SVC can be considered as a synchronous compensator modeled as *PV* bus, with *Q* limits designed by its rated size Qsvc.

The optimal location and design of SVC is formulated as a mixed continues-discrete multi-objective optimization problem. The optimization parameters are the location and size of the SVC.

A. Contingency analysis

Power systems are subjected to contingencies like line outages, generator outages, etc. Contingency analysis is one of the most important functions performed in power systems to establish appropriate preventive and/or corrective actions for each contingency. The system is said to be voltage secure, if the system has sufficient loading margin even after a credible contingency has occurred. Contingency analysis procedure consists of line contingency analysis with detection of overloaded lines and bus voltage violations and ranking the severest contingency cases. The lines are ranked according to the severity of the contingency. In our concern, the severity of the contingency is evaluated from the voltage security point of view, in terms of its resulting in voltage violations and reduced load margin.

B. Objectives

As the main objective of this work is to determine the optimal location and the optimal parameter setting of the SVC in the power network to eliminate or minimize the risk of voltage violations and the voltage stability margin under the most critical single contingencies, the objectives selected for this study are presented below.

1) Voltage Stability Enhancement

Voltage stability enhancement is achieved through maximizing the Static Voltage Stability Margin or Loading Margin, which is the most widely accepted index for proximity of voltage collapse. It is defined as the largest load change that the power system may sustain at a bus or collective of buses from a well defined operating point (base case). The maximization of voltage stability margin can be presented as follows:

$$\text{Maximize } \lambda \tag{8}$$

where λ is the value of loading factor at the critical point or static voltage stability margin. The method used for this margin calculation is the continuation power flow (CPF) [1]. The loads are increased gradually and the power sources will compensate for this increase by increasing its generation. At every load level, the system state is calculated until the maximum or critical condition is reached. In order to assess and enhance voltage security conditions, λ is then evaluated in case of all credible contingencies using CPF.

2) Voltage Deviation

To have a good voltage performance, the voltage deviation at each load bus must be made as small as possible. The voltage deviation to be minimized is as follows [12]:

$$VD = \sum_k (V_k - V_{refk})^2 \tag{9}$$

where V_k is the voltage magnitude at load bus *k* and V_{refk} is the nominal or reference voltage at bus k.

3) Real Power Losses

This objective is to minimize the real power loss in the transmission lines and which can be expressed as:

Minimize P_L,

$$P_L = \sum_{k=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j) \right] \tag{10}$$

where, *nl* is the number of transmission lines; g_k is the conductance of the *kth* line; $V_i\angle\delta_i$ and $V_j\angle\delta_j$ are the voltages at the end buses *i* and *j* of the *k*th line, respectively.

C. Constraints

The equality constraints represent the typical load flow equations as follows:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j) \right] = 0, \quad i = 1, \ldots, NB \tag{11}$$

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$$Q_{G_j} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin\left(\delta_i - \delta_j\right) - B_{ij} \cos\left(\delta_i - \delta_j\right) \right] = 0,$$
$$i = 1,..., NB \qquad (12)$$

where, NB is the number of buses; P_G and Q_G are the generator real and reactive power, respectively; P_D and Q_D are the load real and reactive power, respectively; *Gij* and *Bij* are the transfer conductance and susceptance between bus *i* and bus *j*, respectively.

The inequality constraints represent the system operating limits like limits on reactive generation and bounds on tap settings of transformers.

V. Simulation Results

The MOPSO algorithm and all calculation programs used in this study were written in Matlab7.0 and used to perform the optimization routines. The application is carried out on the IEEE 14-bus test system [16], which consists of two generators, located at bus 1 and 2; three synchronous compensators used only for reactive power support at buses 3, 6 and 8. The generators are modeled as PV buses with Q limits; the loads are typically represented as constant PQ loads with constant power factor, and increased gradually according to:

$$\begin{cases} P_L = \lambda P_{0L} \\ Q_L = \lambda Q_{0L} \end{cases} \qquad (13)$$

where, P_{0L} and Q_{0L} are the active and reactive base loads, whereas P_L and Q_L are the active and reactive loads at a bus L for the current operating point as defined by loading factor λ. Using the CPF method with tangent predictor step and perpendicular corrector step, the bifurcation point corresponding to the voltage collapse condition can be determined. In all MOPSO runs, the population size is N=120 and the maximum number of iterations is set equal to 100.

A. *Contingency analysis*

With the increasing of the system loading condition, the power system is stressed gradually to the critical point where the power system will lose its voltage stability. This condition, determined first for the base case, is reached at λ=1.7204. Then, a contingency analysis was carried out. For each single line outage, the voltage violation buses and the critical loading factor are found. The voltage violations are considered in case of heavy load (20% over the initial load) instead of initial load in order to obtain violations (at initial or light load there are no violations even for line outages). These violations are the limits 0.95 and 1.05 pu on load buses. The results are shown in Table I. According to these results, the most severe contingencies were the outages of lines (1–2), (2–3), and (1–5) with critical loading factors respectively equal to 0.7795, 1.2802 and 1.3326. For the line (1-2) outage, there is no solution for the initial load level and it was necessary to take as initial operating point λ = 0.6.

According to this initial CPF runs and based on the maximum value of the tangent associated to voltage variation at the collapse point, bus 14 is the first most sensitive bus and seems needing Q support (tangent= 0.1049 for the base case). It can be selected as a suitable placement for the SVC to the power system voltage stability enhancement.

Table I
Critical single line outages

Line outage	Voltage violation buses	VS margin
-	-	1.7204
1-2	-	0.7795
2-3	4,5,9,10,14	1.2802
1-5	4,5,6	1.3326

B. *Optimal Location of SVC*

The goal is to find the best location of SVC which is needed to eliminate or minimize the bus voltage violations and maximize load margin under single contingencies. The optimization is made on two parameters: location and size. The SVC size limits are fixed at the beginning. In doing so, the SVC is considered as a synchronous compensator with a reactive power changing continuously between 0 and 2 pu. The optimal location of SVC is considered as a discrete decision variable, where all load buses are candidates to be the optimal location of SVC. The problem is formulated as bi-objective optimization considering the minimization of real power losses and the maximization of VS margin. Here, the VS improvement and power loss minimization are done at the same time. Then, the power losses are calculated at the critical point.

Using the developed program for the MOPSO algorithm explained in section III, Fig. 1 depicts the non-dominated solutions of optimal location and size of SVC. It provides nondominated solutions where corresponding locations are as follows: bus 4 location represents more than 93% of cases with different sizes, 3% of solutions for bus 7, 3% of solutions for bus 9 and the remaining for bus 5 with size limit of 2 pu. The same locations were found for the critical contingencies but with very affected VS margin.

As mentioned previously, the sensitivity of the voltage variation with respect to the loading factor at the critical point suggests incorporating SVC at bus 14. To verify the effectiveness of the proposed method, CPF runs are performed for cases where SVC is located at bus 14 and other at bus 9 which results from the optimization method. Fig. 2 shows clearly that bus 9 is more effective than bus 14 with respect to VS margin. It also gives the optimal size of the SVC installed at this location since it converges for a constant value even if we inject more reactive power. This optimal value couldn't be obtained from the optimization procedure because of the limits considered at the beginning. The same result is obtained for the other optimal locations but for bus 4, the optimal size is very large and is not realist (more than 5 pu). Thus, we have to limit the size at an acceptable value for a needed security margin, e.g., a distance about 20% over the base case to the voltage collapse point without voltage violations.

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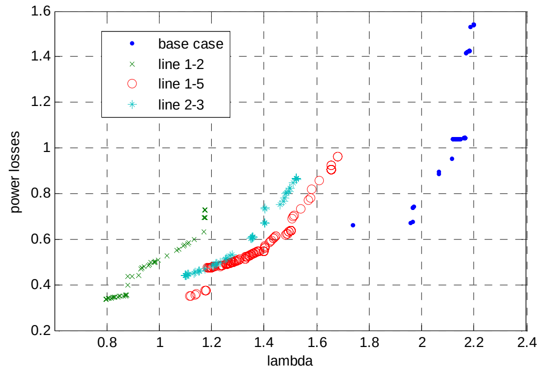

Fig. 1. SVC allocation for base case and critical contingencies

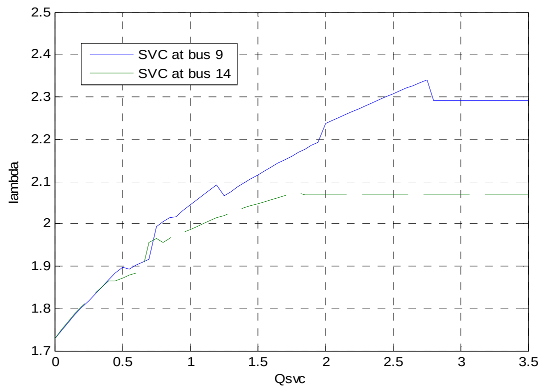

Fig. 2. VS margin for different SVC location

Comparisons between critical load margin and voltage violations buses before and after placing SVC with an optimal solution are shown in Table II. It can be seen that most of the voltage violations buses are eliminated by the installation of the SVC. Although the SVC could not eliminate all bus voltage violations, significant number of them is eliminated and the voltage profile in the rest of buses is significantly enhanced. For line 2-3 outage and before using SVC, five buses have low voltage violation. After using SVC installed at bus 9, four of them are eliminated and the violation for the fifth bus is reduced (from 0.04 to 0.0122 pu at bus 4).

Table II
Voltage violations and VS margin
with and without SVC installation

	w/o SVC		SVC at bus 9		SVC at bus 4	
Line outage	Voltage violations buses	VS margin	Voltage violations buses	VS margin	Voltage violations buses	VS margin
-	-	1.7204	-	2.2354	-	2.1682
1-2	-	0.7795	4,5	1.1330	-	1.2855
2-3	4,5,9,10, 14	1.2802	4	1.4269	-	1.6487
1-5	4,5,6	1.3326	4,5	1.7539	-	1.7944

C. *Three objective case*

This case is more complicated than the previous one, where three objectives are considered namely: VS margin, power losses and voltage deviations. The location and size of SVC is considered, which maximizes the VS margin and minimize the P_L and VD.

Fig. 3 presents non-dominated solutions for the optimal location and size of SVC. The optimal locations obtained are buses 4, 5, 9 and 10. If P_L is priority, the optimal location of SVC may be bus 4 or 5, while if the VS margin is priority than other objectives, SVC with 2 pu of size installed at bus 9 or 10 should be the optimal choice. In the case where the VD is priority, SVC installed either at bus 5 or bus 10 may be a good choice.

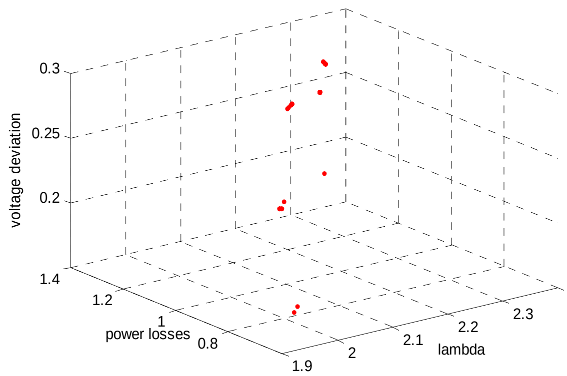

Fig. 3. Three objectives SVC allocation

VI. Conclusion

In this paper, the optimal location of SVC was used in order to improve the VS margin, minimize load voltage deviation and reduce power losses under single line contingencies. The problem is formulated as a mixed discrete-continuous multi-objective optimization problem. Simulations performed on IEEE 14-bus test system indicate that the proposed method is able to provide optimal locations of these kinds of FACTS devices to achieve voltage security enhancement. As an illustrative example, an optimal location solution was compared using conventional CPF routine which confirmed the effectiveness of the proposed method.

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