Curved Space Optimization for Allocation of SVC in a Large Power System

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Abstract-- This paper investigates the ability of a new heuristic optimization method known as Curved Space Optimization (CSO) to deal with optimal placement of Static Var Compensators (SVCs) in a large power system based on its primary function, where the optimization is made on two parameters: its location and size. The primary function of a SVC is to improve transmission system voltage, thereby enhancing the maximum power transfer limit. To validate the results obtained by CSO, Particle Swarm Optimization (PSO) Algorithm is applied. The results show CSO finds the optimal solution in finding the location and size of SVC.

Key-Words -- Curved Space Optimization, Particle swarm optimization, Voltage stability, Power system, FACTs devices, SVC.

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1 Introduction

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown by many researches that these algorithms are good replacement as tools to solve complex computational problems. Various heuristic approaches have been adopted by researches including genetic algorithm, tabu search, simulated annealing, ant colony and particle swarm optimization.

Due to many good features of GA techniques, GA has been widely applied in applications, such as optimization of objective functions, training neural networks, tuning fuzzy membership functions, machine learning, system identification, control, etc. Also, study on the use of genetic algorithm to seek the optimal location of FACTS devices in a power system is carried out by the researches around the world [1]-[9].

Recently, Kennedy and Eberhart introduced the Particle Swarm Optimization (PSO) method as an evolutionary computation technique [10]. The original version of the PSO operates in continuous space [10] was extended to operate on discrete binary variables [11]. The PSO has been proven to be very effective for static and dynamic optimization problems. For the first time, the PSO is applied in power systems in 1999 [12], and has been successfully applied to various problems such as power system stabilizer design, reactive power and voltage control, and dynamic security border identification.

Curved Space Optimization (CSO), was introduced by Farrahi-Moghaddam [13] and in this paper the capability of this algorithm in solving a problem is investigated.

In the last decades, efforts have been made to find the ways to assure the security of the system in terms of voltage stability. It is found that flexible AC transmission system (FACTS) devices are good choices to improve the voltage profile in power systems that operate near their steady-state stability limits and may result in voltage instability. Many studies have been carried out on the use of FACTS devices in voltage and angle stability. Taking advantages of the FACTS devices depends greatly on how these devices are placed in the power system, namely on their location and size.

In view of this, this paper considers the problem of placing SVC using CSO and PSO in a large power system to maintain the nodal voltage magnitudes. The problem formulation is how to place SVC that provides compensation for reactive power in a power system. For this, SVC is placed in a large power system based on its primary function, which is the voltage stability.

2 Voltage Stability Analysis

Voltage stability is the ability of a power system to maintain acceptable voltages at all buses in the system not only under normal operation, but also after following disturbances. Voltage stability can be categorized as large-disturbance and small-disturbance voltage stabilities. Large–disturbance voltage stability is the ability of the system to control the voltage after being subjected to large disturbances such as system faults, and loss of load or generation. Small signal voltage stability is the ability of the system to control voltage after being subjected to small perturbations, such as gradual changes in loads [14].

In this paper two techniques are used for analysis of voltage stability, which are briefly explained below:

2.1 CSO algorithm

The first step is initialization where the first generation (*n*) is distributed randomly over all of variables space. Any member of population is known as mass. Then the fitness will be computed for each mass. In CSO finding the best solution in each generation and moving to the next generation is done as follows: the CSO algorithm draws curves for the variables space around the masses (*n*) according to its fitness (this is very similar to the relativity theory for mass and space). Therefore, we have a space with *n* curves where, at some places, the curvature is very high, and there are some regions in which the curvature is very small. On the other hand, a fitness is calculated for each mass. For a mass with higher fintness the curvature is higher comparing to the other masses. Consider a transformation, $x' = A(x)$ that can define the curvature for each mass. The old axis is defined by x, and the new axis defined by x'. There is a transformation, $x' = A(x)$, which relates the x values to the x' values according to the curvature of the space. The new points are selected randomly from the x' axis instead of the x axis. In fact, in each step the axis and its curvature are changed by considering $x' = A(x)$. Then, the selected points are transforms from the x' axis to the x axis using $A(x)$. These new x points are the new selected points in x space. It is obvious that the new points are accumulated around the high-fitness points of the previous generation.

At the first stage of the algorithm, the dominance of the curvatures will be large in order to cover the entire space variable. As the algorithm continues, the dominance of the curvatures will be reduced. For this, a radius of dominance is defined as ρ in which the radius is reducing by following equation:

$$\rho^d{}_{i+1} = \alpha\rho_i \qquad d = 1,2,\ldots,D \tag{1}$$

where α is a parameter between 0 and 1 and d is the dimension of the problem.

As it was discussed in the previous subsection, in CSO algorithm, in each step, the axes of the variables space are changed. In the other words, the variables space is changed, and this change must be computed from the transformation function $A(x)$, which is needed to obtain the next generation. In order to reduce the computational cost of algorithm, we can find some ways which give the results without any need to the explicit form of $A(x)$. For doing so, the curvature idea is replaced with some other techniques which have the same effects in selection of new points. The technique is based on the introduction of a probability function over the variables space.

In the simplest case, the probability function can be considered as a number of hyper-cubes which every of them is around one of the previous generation points (masses). The dimensions of the hyper-cubes are defined according to the dimension of search space and equation (1). At the first stag of the algorithm, the dimension of hyper-cubes is equal to all of the points in the search space defined by following equation:

$$\rho^d = \frac{x_d^{high} - x_d^{low}}{2} \tag{2}$$

The probability function for the i^{th} mass according to the rank of its fitness ($r(i)$) defined as follows:

$$p(i) = \frac{\beta^{-r(i)}}{\sum_{j=1}^{n} \beta^{-j}} \qquad (3)$$

where β is a controllable parameter that controls the selection pressure.
Although, for all values of α there is a chance that the algorithm be trapped around a local minimum. This leads us to the concept of mutation, which used in genetic algorithm. The mutation method which is used in the algorithm is the same as that of genetic algorithm.

2.2 PSO algorithm

PSO is as an optimization tool that provides a population-based search procedure in which individuals, called particles, change their positions with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. Particles in the PSO are defined by two variables: x and v in which x is the position of the particle representing a candidate solution to the problem and v describes the velocity.
In the PSO, two different definitions are used as: 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 known 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 *pbest*, the i^{th} particle velocity in the d^{th} dimension is updated according to the following equation:

$$v_{id}(t+1) = w.v_{id}(t) + c_1.A + c_2.B \qquad (4)$$

where ,

$A = rand\,(pbest_{id} - x_{id}(t))$,

$B = Rand\,(gbest_{id} - x_{id}(t))$,

w is inertia weight factor, c_1 and c_2 are acceleration constant, $rand()$ and $Rand()$ are random number between 0 and 1.
Based on the updated velocities, each particle changes its position according to the following equation:

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (5)$$

3 Study system

A 5-area-16-machine system: The study system is shown in Fig. 1, consisting of 16 machines and 68 buses. This is a reduced order model of the New England (NE) New York (NY) interconnected system. The first nine machines are the simple representation of the New England system generation. Machines 10 to 13 represent the New York power system. The last three machines are the dynamic equivalents of the three large neighboring areas interconnected to the New York power system.
Modal analysis, CSO and PSO are used to locate SVC optimally in the power system shown in Fig. 1. Implementations of the two different techniques are presented below.

Placing of SVC using CSO and PSO starts from an initial load. All loads are increased gradually near to the point of voltage collapse, all at once. Fig. 2 shows the profile of the voltage when system is heavily stressed and is reached to the point of collapse.

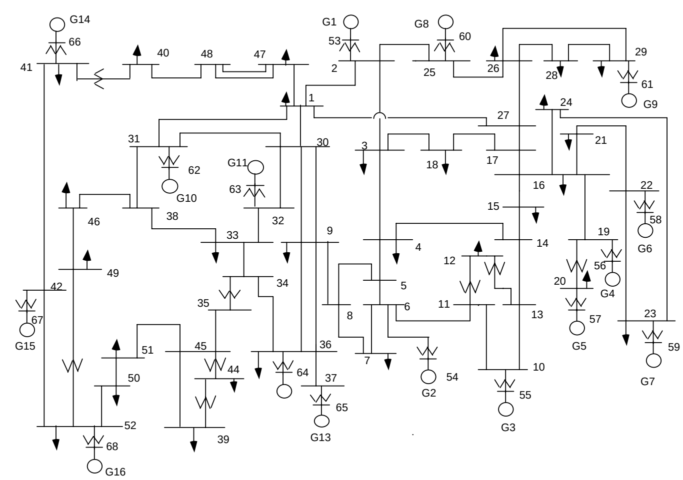

Fig. 1. Single line diagram of a 5-area study system.

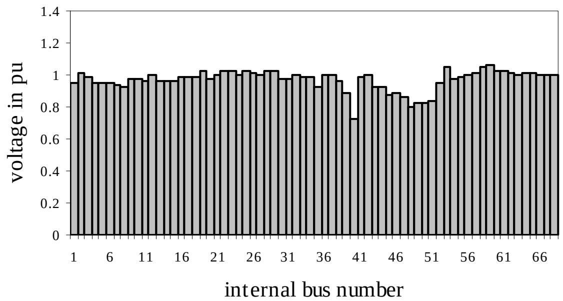

Fig. 2. Bus voltage magnitude profile when system is heavily stressed.

The goal of the optimization is to find the best location of SVC where the optimization is made on two parameters: their location and size. Therefore, a configuration is considered with two dimensions. The number of masses is set to be 50 that are generated randomly.

In this paper SVC is placed based on its primary function, which is the voltage stability. For a level of loads, the following objective function is minimized:

$$obj = \sum abs\left|V_i - V_{ref\,i}\right|^6 \qquad (6)$$

where V_i is the voltage magnitude and V_{refi} is the nominal voltage at bus i.

In this paper, α is considered to be 0.9 and β is set to be 1.2. Also, the number of iteration is considered to be 70, which is the stopping criteria.

In the PSO algorithm, n particles are generated randomly where n is selected to be 50. Since optimizations are made on two parameters: its location and size, therefore, each particle is a d-dimensional vector in which $d = 2$. The initialization is made on the position randomly for each particle.

As in the CSO, the number of iteration is considered to be 70. The parameter in (4) must be tuned. These parameters control the impact of the previous velocities on the current velocity where, in this paper, $c_1 = c_2 = 2$ and w is decreasing linearly from 0.9 to 0.1.

Each particle in the population is evaluated using the objective function defined by (6), searching for the particle associated with obj_{best}. The best previous position of the i^{th} particle is recorded and represented as: $pbest_i = (pbest_{i,1}, pbest_{i,2})$ and the index of the best particle among all of the particles in the group is for the *gbest*.

Using the *gbest* and *pbest*, particle velocity and position is updated according to (4) and (5)..

To locate SVC by CSO and PSO, suitable buses are selected based on 20 independent runs, under different random seeds. At the end of the 20 independent runs, the following results are observed by CSO: 90% of the results show that the SVC should be placed at bus 40 with 145 MVAr size; 10% of the results show that the SVC should be placed at bus 48. Also, the following results are observed by PSO: 80% of the results show that the SVC should be placed at bus 40 with 145 MVAr size; 20% of the results show that the SVC should be placed at bus 48. Fig. 3 shows bus voltage magnitude profile of the stressed system after placing a 145 MVar SVC at bus 40.

The results obtained by CSO and PSO are averaged over independent runs. The average best-so-far of each run are recorded and averaged over 20 independent runs. To have a better clarity, the convergence characteristics in finding the location and size of a SVC is given in Fig. 4. These figures show that CSO has a good capability to find optimal solution.

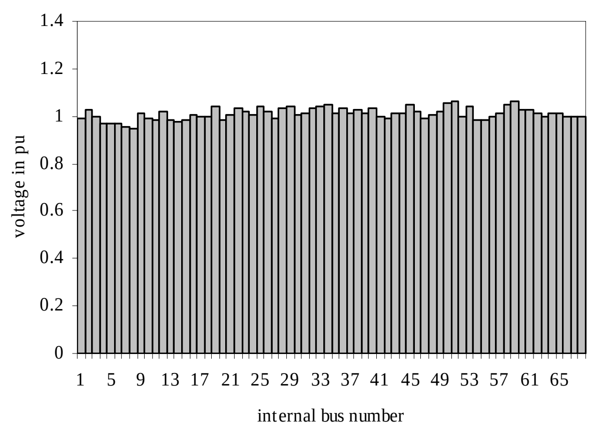

Fig. 3. Bus voltage magnitude profile of the stressed system after placing 145 MVar SVC at bus 40.

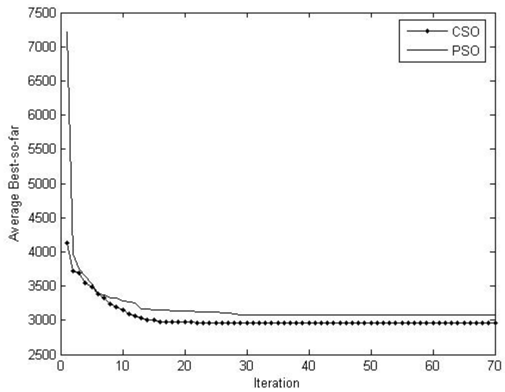

Fig. 4. Convergence characteristics of CSO and PSO on the average best-so- far in finding the solution, 145 MVar SVC at bus 40.

4 Conclusion

In this paper, CSO and PSO are applied to place SVC in a power system. CSO and PSO identify the same bus that is vulnerable to the voltage collapse. Both CSO and PSO give the same level of compensation for the SVC. Although the results obtained by SVC and PSO are the same but CSO quickly finds the high-quality optimal solution in finding the location and size of SVC. The obtained result shows that CSO has a great potential in solving complex power system problems and should be applied to other problems. To have an optimal placement for SVC, multi-objective VAr planning should be considered which, is the future work of the authors.

References

[1] P. Paterni , S. Vitet, M. Bena and A. Yokoyama, "Optimal location of phase shifters in the French network by genetic algorithm", *IEEE Trans. Power Systems*., vol. 14, pp. 37–42, 1999.

[2] H.C. Leung and T.S. Chung, "Optimal placement of FACTS controller in power system by a genetic based algorithm" *in Proc. 1999 IEEE Power Electronics and Drive Systems Conferenc*e, Vol. 2, pp.833 – 836.

[3] Z.Y. Dong, Y. Wang, D.J. Hill and Y.V. Makarov, "A new approach to power system VAr planning aimed at voltage stability enhancement with feedback control" *in Proc. 1999 IEEE International Conference on Electric Power Engineering, PowerTech Budapest* , pp. 33.

[4] S. Gerbex, R. Cherkaoui and A.J. Germond, "Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms", *IEEE Trans. Power Syst*., vol. 16, No. 3, pp. 537–544, August 2001.

[5] F. Wang and G.B. Shrestha, "Allocation of TCSC devices to optimize total transmission capacity in a competitive power market" *in Proc. 2001 IEEE Winter Meeting*, Vol. 2, pp. 587 – 593.

[6] E.E. El-Araby, N. Yorino and H. Sasaki, "A comprehensive approach for FACTS devices optimal allocation to mitigate voltage collapse" *in Proc. 2002 IEEE Transmission and Distribution Conference*, pp.62 – 67.

[7] L.J Cai, I. Erlich and G. Stamtsis, "Optimal choice and allocation of FACTS devices in deregulated electricity market using genetic algorithms" *in Proc. 2004 IEEE PES General Meeting* , pp. 201 - 207.

[8] N.P. Padhy, M.A. Abdel-Moamen and B.J. Praveen Kumar, "Optimal location and initial parameter settings of multiple TCSCs for reactive power planning using genetic algorithms" *in Proc. 2004 IEEE PES General Meeting*, pp. 1110 – 1114,

[9] L. Ippolito and P. Siano, "Selection of optimal number and location of thyristor-controlled phase shifters using genetic based algorithms" *IEE Proc.-Gener., Transm. Distrib*., Vol. 151, No. 5, pp. 630 – 637, September 2004.

[10] J. Kennedy and R. Eberhart, "Particle swarm optimization," *in Proc. 1995 IEEE Int. Conf. Neural Networks (ICNN'95)*, vol. IV , pp. 1942–1948.

[11] J. Kennedy, "The particle swarm: Social adaptation of knowledge," *in Proc. 1997 IEEE Int. Conf. Evol. Comput.* , pp. 303–308.

[12] H Yoshida, Y. Fukuyama, S. Takayama and Y. Nakanishi, "A particle swarm optimization for reactive power and voltage control in electric power systems considering voltage security

assessment" in Proc. 1999 IEEE International Conference SMC ,Vol. 6, pp:497 – 502.

[13] F. Farrahi-Moghaddam, "Curved Space Optimization (CSO): A novel approach to heuristic optimization" in Proc, 12th CSICC2007, Iran, Feb, 2007.

[14] P. Kundur, *Power System Stability and Control,* McGraw-Hill: New York, 1994.