



## Optimal Allocation of Static VAR Compensator for Active Power Loss Reduction by Different Decision Variables

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**Abstract**— An optimization technique based on particle swarm optimization (PSO) algorithm is developed in this paper to determine the optimal allocation of static VAR compensator (SVC) in transmission systems. The objective function is to minimize the total system active power loss. In the optimization process, either SVC reactive power or voltage at SVC connection point can be entered into a decision variable to define the optimal sizes of SVC. A case study is conducted with a modified IEEE 14-bus system. The effectiveness of the proposed technique is demonstrated by the obtained optimal solutions which satisfy all the specified constraints while keeping the total system active power loss at minimum. The test results also reveal that both SVC reactive power and voltage at SVC bus can provide similar strategies for optimal SVC placement when they are applied as the decision variable. The differences between using these two variables are the information of SVC required for computation and power flow solution to be performed in the solution algorithm. In addition, the economic benefit of optimal SVC allocation for active power loss reduction is evaluated using the energy loss cost and the investment cost of SVC.

**Keywords**— FACTS devices, Loss reduction, Particle swarm optimization, Static VAR compensator, SVC.

### 1. INTRODUCTION

Flexible AC Transmission System (FACTS), as defined by IEEE, is an alternating current transmission system incorporating with power electronic-based devices or other static controllers to enhance the performance of the transmission network [1]. Two basic objectives for the applications of FACTS are to increase power transfer capability and to control power flow of the transmission system. The achievement of these two objectives significantly increases the efficient utilization of the existing facilities in the transmission network. In general, FACTS devices or FACTS controllers can improve controllability and increase power transfer capability of the transmission system by controlling of one or more AC transmission system parameters, e.g. voltage magnitude, phase angle, line impedances.

Nowadays, many types of FACTS devices are practically applied to transmission networks; such as static synchronous compensator (STATCOM), static VAR compensator (SVC), thyristor controlled series capacitor (TCSC), thyristor controlled phase shifting transformer (TCPST), unified power flow controller (UPFC). Their basic applications, for example, are voltage control, power flow control, reactive power compensation, increase of transmission capability, system stability and security improvement, power quality

improvement, and power conditioning [2]. This paper only focuses on one commercial shunt type FACTS device, namely, SVC due to its advantage on rapid and continuous response to improve the performance of the network.

The SVC is a shunt connected static generator or absorber whose output is adjusted to exchange capacitive or inductive current so as to maintain or control specific parameters of the electrical power system, typically bus voltage [1]. By the definition, the SVC behaves like a shunt-connected variable reactance, which either generates or absorbs reactive power in order to control voltage at the point of connection [3].

The SVC is primarily for reactive power compensation to provide power loss reduction and voltage profile improvement. To achieve such benefits, it is necessary to simultaneously determine the optimal numbers, locations, and sizes of SVC. The SVC placement problem, therefore, is a large scale combinatorial optimization problem which mathematically formulated with continuous and discrete variables as well as discontinuous, non-differentiable and non-linear equations. With such a feature of the problem, the conventional optimization algorithms find it difficult to seek for the optimal solution.

An efficient tool to solve this type of problem is heuristic methods. The searching process of a heuristic method finds better solutions by moving from one solution to another solution using appropriate rules. Several heuristic methods have been developed to handle difficult optimization problems in science and engineering fields. Among them, popular methods are genetic algorithm (GA) [4], tabu search (TS) [5], simulated annealing (SA) [6], and particle swarm optimization (PSO) [7].

GA is based on natural selection rules. It uses genetic operators such as selection, crossover, and mutations to define new solutions in probability way. GA requires

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The authors would like to express his grateful thanks to Ministry of Science and Technology (MOST)-Thailand, Coordinating Center for Thai Government Science and Technology Scholarship Students (CSTS)-Thailand and Thailand Institute of Scientific and Technological Research (TISTR) - Thailand for their supports.

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long computation time and may be converge prematurely to a suboptimal solution. TS is based on deterministic search that identifies an optimal solution using an adaptive memory called tabu list. The implementation of TS is time consuming when solving an optimization problem with continuous variables. In SA, a parameter called cooling schedule is introduced to shrink the search space gradually. Although SA has an ability to search for an optimal solution, its parameters in calculation are difficult to determine and it often takes a long computation time to search for the optimal solution. PSO is an optimization technique derived from simulation of a simplified social model of swarms (e.g., bird flocks or fish schools). The interaction of particles in swarm guides the direction of swarm towards the optimal regions of the search space. The main advantages of PSO are simple concept, easy implementation, robustness to control parameters, less computation time, and computationally efficiency when compared with mathematical algorithms and other heuristic optimization techniques [8].

To solve the SVC placement problem by PSO, each particle, which is referred as a candidate solution, should consist of two segments. In the first segment, it is only bus number which can be used as the decision variable to discover the optimal locations of SVC. On the other hand, either reactive power of SVC or voltage magnitude at SVC connection point can be applied as the decision variable in the second segment to define the optimal sizes of SVC. Case study with a modified IEEE 14-bus system is conducted in this work to demonstrate the effectiveness of PSO algorithm and to compare the optimal choice for SVC placement obtained by using reactive power of SVC and voltage at SVC bus as a decision variable.

## 2. MODELLING OF SVC

The SVC consists of a bank of capacitors in parallel with a thyristor-controlled reactor (TCR) [3]. With fast control action by thyristor switching of the TCR, the SVC has a nearly immediate speed of response to vary its reactive power with the purpose of voltage control. For balanced operation and balanced SVC designs, a single-phase SVC model is represented by its positive sequence model as depicted in Figure 1(a) [9].

To calculate the value of SVC equivalent reactance ( $X_{SVC}$ ), TCR inductive reactance ( $X_L$ ) and the value of TCR firing angle (designated as  $\alpha_{SVC}$ ) are used to find the TCR equivalent reactance ( $X_{L-TCR}$ ) by Eq.(1) as [10]:

$$X_{L-TCR} = \frac{\pi X_L}{\alpha_{eq}} \quad (1)$$

$$\alpha_{eq} = 2(\pi - \alpha_{SVC}) + \sin(2\alpha_{SVC}) ; \frac{\pi}{2} \leq \alpha_{SVC} \leq \pi \quad (2)$$

$X_{SVC}$  is then determined by the parallel combination of  $X_{L-TCR}$  and SVC capacitive reactance ( $X_C$ ).

$$X_{SVC} = \frac{X_C X_L}{\frac{X_C \alpha_{eq}}{\pi} - X_L} \quad (3)$$

With any given values of  $X_C$  and  $X_L$ , it is observed in Eqs. (2) and (3) that the value of  $X_{SVC}$  is varied according to the value of  $\alpha_{SVC}$ .

When voltage magnitude at SVC connection point ( $V_{SVC}$ ) is specified, SVC reactive power ( $Q_{SVC}$ ) can be calculated by:

$$Q_{SVC} = \frac{V_{SVC}^2}{X_C X_L} \left\{ \frac{X_C \alpha_{eq}}{\pi} - X_L \right\} \quad (4)$$

$Q_{SVC}$  is at maximum when  $\alpha_{SVC} = \frac{\pi}{2}$  and at minimum when  $\alpha_{SVC} = \pi$ . Assuming  $V_{SVC}$  in Eq.(4) is 1.0 p.u., the maximum and minimum values of  $Q_{SVC}$  are given in Eqs. (5) and (6).

$$Q_{SVC}^{max} = \frac{X_C - X_L}{X_C X_L} \quad (5)$$

$$Q_{SVC}^{min} = -\frac{1}{X_C} \quad (6)$$

Thereby, the SVC can be modeled as a generator (or absorber) of adjustable reactive power shown in Figure 1(b). It should be noted that the SVC injects reactive power into the network when  $Q_{SVC} < 0$ . Conversely, it absorbs reactive power from the network if  $Q_{SVC} > 0$ .

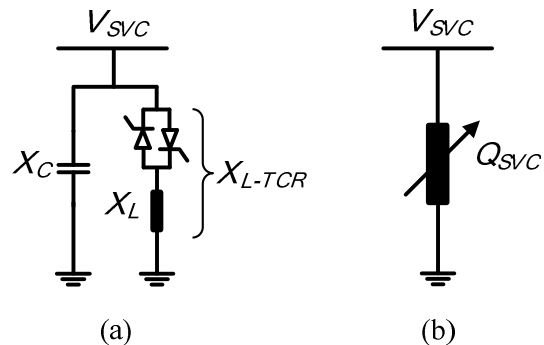


Fig. 1. SVC model.

## 3. POWER FLOW CALCULATION

### 3.1 Conventional Newton-Raphson Method

Power flow or load flow calculation is the computation procedure to determine the steady-state operation of a power system. Power flow study is the core of power system analysis. It can be applied in the designing, planning, operational planning, operation/control, and expansion of a power system [11]. The results obtained from power flow calculation are the magnitude and phase angle of voltage at each bus, active and reactive power flowing in each line, and also system active and reactive power losses.

The conventional Newton-Raphson method is an efficient tool for solving the power flow problem due to its strong convergence characteristic. To apply the Newton-Raphson method for power flow solutions, a set of simultaneous nonlinear equations of active and reactive power, expressed in Eqs.(7) and (8), are formulated by taking the nodal voltage magnitude and phase angles as unknowns [11].

$$P_i = \sum_{j=1}^{NB} |Y_{ij} V_i V_j| \cos(\theta_{ij} + \delta_j - \delta_i) \quad (7)$$

$$Q_i = -\sum_{j=1}^{NB} |Y_{ij} V_i V_j| \sin(\theta_{ij} + \delta_j - \delta_i) \quad (8)$$

$$P_i = P_{G,i} - P_{D,i} \quad (9)$$

$$Q_i = Q_{G,i} - Q_{D,i} \quad (10)$$

- where  $P_i$  = net value of active power at bus  $i$   
 $NB$  = number of buses  
 $Y_{ij}$  = element  $(i, j)$  in bus admittance matrix  
 $V_i$  = voltage at bus  $i$   
 $V_j$  = voltage at bus  $j$   
 $\theta_{ij}$  = angle of  $Y_{ij}$   
 $\delta_i$  = phase angle of voltage at bus  $i$   
 $\delta_j$  = phase angle of voltage at bus  $j$   
 $Q_i$  = net value of reactive power at bus  $i$   
 $P_{G,i}$  = active power generated at bus  $i$   
 $P_{D,i}$  = active power demand at bus  $i$   
 $Q_{G,i}$  = reactive power generated at bus  $i$   
 $Q_{D,i}$  = reactive power demand at bus  $i$

The mismatch vector and the Jacobian matrix are determined in the first iteration from the estimated value of voltage magnitudes and phase angles. The mismatch vector represents the difference of the scheduled and calculated active and reactive powers whereas all elements in the Jacobian matrix are the first-order partial derivatives of active and reactive powers with respect to voltage magnitudes and phase angles. The correction vector, given by the multiplication of the inverse of the Jacobian matrix and the mismatch vector, is employed to update the values of nodal voltages and phase angles. The updated voltages and phase angles are then used to calculate the mismatch vector and the Jacobian matrix for next iteration. The iterative computation process is repeatedly performed until the mismatch vector is less than an acceptable tolerance. The final value of voltages and phase angles at each bus are obtained. More detail about the conventional Newton-Raphson method is explained in [11].

### 3.2 Power Flow Calculation including SVC

There are two approaches to solve the power flow problem with the inclusion of SVC. The first approach treats the SVC located at bus  $m$  as a VAR source which

injects or absorbs reactive power  $Q_{SVC,m}$ . Consequently, the net value of reactive power at bus  $m$  can be calculated by Eq.(11) expressed below

$$Q_m = Q_{G,m} - Q_{SVC,m} - Q_{D,m} \quad (11)$$

Voltage magnitudes and phase angles are still the unknown variables. The buses chosen for SVC placement are defined as load (PQ) bus. The conventional Newton-Raphson method is applied to find the solutions without any modification of the mismatch vector and the Jacobian matrix. In other words, the first approach can solve the power flow problem including SVC by the same computation procedure as in the power flow problem without SVC.

The second approach applied for the power flow problem with SVC is proposed in [3] and [9]. In this approach, the value of SVC firing angle ( $\alpha_{SVC}$ ) is the additional unknown and voltage magnitude at bus with SVC should be specified.

The mismatch vector is still the difference of the scheduled and calculated active and reactive powers. The calculated active power for all bus and the calculated reactive power at bus without SVC remain determined by Eqs. (7)-(10), while the calculated reactive power at bus with SVC is derived by Eqs. (4), (8), and (11). In addition, the Jacobian matrix should be expanded to include the partial derivatives of active and reactive powers with respect to  $\alpha_{SVC}$ .

The multiplication of the inverse of the augmented Jacobian matrix and the mismatch vector provides the information of the correction vector. The current values of voltages, phase angles, and firing angles are then updated by the correction vector in order to calculate active and reactive powers in the next iteration. The calculation process is repeated and will terminate by the same criteria as in the conventional Newton-Raphson method.

It should be noted that the first approach (treating SVC as VAR source) needs only the operating limits of SVC reactive power for power flow calculation. The second approach (adding  $\alpha_{SVC}$  for unknown) essentially requires voltage magnitudes at buses with SVC and parameters of SVC (i.e.  $X_C$ ,  $X_L$ , and operating limits of  $\alpha_{SVC}$ ) to run power flow calculation.

## 4. PROBLEM FORMULATION

The aim of SVC placement in this work is to minimize the total system active power loss. The objective function is:

$$Min F = \sum_{k=1}^{NL} P_k \quad (12)$$

The objective function is subjected to the following equality and inequality constraints.

- Power balance equations as in Eqs. (7)-(8).
- Bus voltage limits.

$$V^{\min} \leq V_i \leq V^{\max} \quad (13)$$

- Limits of reactive power generated at voltage-controlled (PV) buses.

$$Q_{G,i}^{\min} \leq Q_{G,i} \leq Q_{G,i}^{\max}; i \in PV \text{ buses} \quad (14)$$

- Limits for reactive power of SVC.

$$Q_{SVC}^{\min} \leq Q_{SVC,m} \leq Q_{SVC}^{\max} \quad (15)$$

- Operating range of SVC firing angle.

$$\frac{\pi}{2} \leq \alpha_{SVC,m} \leq \pi \quad (16)$$

- SVC must be installed at load (PQ) buses

$$m \in N_{PQ} \quad (17)$$

where  $F$  = the value of objective function  
 $NL$  = number of lines  
 $P_k$  = active power loss in line  $k$   
 $i$  = bus number  
 $m$  = bus number where SVC is located  
 $\min$  = lower limit of variable being considered  
 $\max$  = upper limit of variable being considered  
 $V$  = bus voltage magnitude  
 $Q_{G,i}$  = reactive power generated at bus  $i$   
 $Q_{SVC}$  = reactive power of SVC  
 $\alpha_{SVC}$  = firing angle of SVC  
 $N_{PQ}$  = set of load bus

## 5. PARTICLE SWARM OPTIMIZATION (PSO)

PSO, originally invented in 1995, is a population based stochastic optimization technique. In PSO, the population is called "swarm" and the individual in swarm is called "particle". The swarm of particles is employed to conduct the searching process to find the optimal solution. Each particle is represented by its position and velocity and is referred as a potential solution in  $n$ -dimensional search space of the problem. Particles have knowledge of formerly moved directions, their previous best solutions, and the best solution found by the best particle in swarm. Based on this knowledge, particles can explore different regions of search space to locate a good optimum.

The positions and velocities of the initial swarm are randomly generated at the outset. This first step allows all particles to arbitrarily distribute across the search space. The fitness value of particle is evaluated in the next step to determine the best position of each particle and also to reveal the particle that has the best global fitness value in the current swarm.

Next, the velocities of all particles are updated from current iteration ( $t$ ) to the next iteration ( $t + 1$ ) by: [12]

$$v_{id}(t+1) = wv_{id}(t) + c_1r_{1d}(t)[y_{id}(t) - x_{id}(t)] + c_2r_{2d}(t)[\hat{y}_d(t) - x_{id}(t)] \quad (18)$$

where  $v$  = velocity of particle  
 $x$  = position of particle  
 $w$  = inertia weight  
 $c_1, c_2$  = positive acceleration constants  
 $r_{1d}, r_{2d}$  = uniformly distributed random values in the range [0,1]  
 $y$  = personal best position;  $Pbest$   
 $\hat{y}$  = global best position;  $Gbest$   
 $i$  =  $i^{th}$  particle  
 $d$  =  $d^{th}$  dimension  
 $id$  = particle  $i$  in dimension  $d$

The first term in the right hand side of Eq.(18) is an inertia weight from the current velocity. The second term represents the knowledge based on the best solution of each particle while the third term is the information of the best solution found by the best particle in swarm.

Position update is the last step. The new position of each particle is calculated by:

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (19)$$

The step of fitness value evaluation including the step of velocity and position updating are repeated until a stopping criterion is met (for example, maximum number of iteration is reached, an acceptable solution is found, or no improvement in solution is observed over a number of iterations) and the optimal solution is obtained. More explanations about PSO algorithm can be found in [12].

## 6. SOLUTION ALGORITHM

### 6.1 Decision Variables

Two decision variables are required to solve SVC allocation problem. The first one is for the optimal locations of SVC and the second one is for the optimal sizes of SVC reactive power at each location.

Bus number, a discrete variable, is the decision variable to discover the suitable locations of SVC placement. In opposition, either SVC reactive power ( $Q_{SVC}$ ) or voltage magnitude at SVC connection point ( $V_{SVC}$ ) can be selected as a decision variable to determine the optimal sizes of SVC. Both  $Q_{SVC}$  and  $V_{SVC}$  are continuous variables.

When  $Q_{SVC}$  is the decision variable, the constraint (16) is omitted and the optimal sizes of SVC reactive power are directly defined by the optimal solution. Conversely, when  $V_{SVC}$  is entered as the decision variable, the constraint (15) can be discarded and the obtained optimal solution proposes the suitable voltage magnitudes at SVC buses. To determine the optimal sizes of SVC reactive power, power flow calculation including SVC by the second approach (mentioned in

Section 3.2) must be carried out to find the values of  $\alpha_{SVC}$  from  $V_{SVC}$  provided by the optimal solution. After that, SVC reactive power is calculated by Eq.(4) using the values of  $\alpha_{SVC}$ ,  $V_{SVC}$ , and SVC parameters.

**6.2 Particle's Representation**

The optimal solution of SVC placement simultaneously defines the optimal sites and sizes of SVC that meet the requirement of the desired objective function while satisfying all the constraints. Consequently, each particle in swarm consists of two segments. The first segment corresponds to the location information of SVC while the second segment represents the setting values of SVC. The dimension of each segment is  $n_{SVC}$ , which is the given number of SVC to be optimally installed. Thereby, the total dimension of particle is  $2n_{SVC}$ .

For particle coding, each digit in the first segment represents a bus number where a SVC is located. Each digit of the second segment could be either  $Q_{SVC}$  or  $V_{SVC}$  at each bus found in the first segment. Bus numbers accommodated in the first segment should be load bus and can not be repeated to ensure that there is only one SVC at a bus whereas the values of  $Q_{SVC}$  or  $V_{SVC}$  in the second segment should be maintained within their operation limits.

**6.3 Selection of Feasible Solution**

Bus numbers in the first segment of particle should be complied with two criteria; 1) they must be the member in the set of load (PQ) bus and 2) they can appear only once. Therefore, every particle in swarm should be classified into the qualified and unqualified particle. The qualified particles are those which do not violate the two criteria mentioned above. Otherwise, they are the unqualified particles and will be discarded. This step greatly helps reduce the computational burden because power flow calculations are only performed for the qualified particles.

**6.4 Computation Procedure**

The computation procedure, developed based on PSO algorithm, for optimal SVC allocation is described by the following steps:

- Step 1: Input line data and bus data of a system, SVC's parameters, all operational constraints and PSO parameters.
- Step 2: Select a decision variable for optimization process and then generate an initial population of particles. The information contained in the particles depends on the chosen decision variable.
- Step 3: Set iteration index  $t = 0$ .
- Step 4: Identify the qualified and unqualified particles by checking bus number appeared in the first segment of all particle.
- Step 5: For each qualified particle, perform power flow calculation to obtain all bus voltages including active and reactive power losses.
- Step 6: Check all the constraints. If any of the

constraints is violated, a penalty term is then applied, or else a penalty term is zero.

- Step 7: Evaluate the fitness value of qualified particle using the sum of active power loss and penalty term.
- Step 8: Compare the fitness value of qualified particle with the personal best,  $Pbest$ . If the fitness value is lower than  $Pbest$ , set this value as the current  $Pbest$ , and record the particle position corresponding to this  $Pbest$  value.
- Step 9: Select the minimum value of  $Pbest$  from all qualified particles to be the current global best,  $Gbest$ , and record the particle position corresponding to this  $Gbest$  value.
- Step 10: Update the velocity and position of all particles.
- Step 11: If the maximum number of iterations is reached, the particle associated with the current  $Gbest$  is the optimal solution and then go to Step 12. Otherwise, set  $t = t + 1$  and return to Step 4.
- Step 12: Print out the optimal solution.

**7. CASE STUDY**

The IEEE 14-bus system, depicted in Figure A1 [13] of the appendix, is modified to be the test system for case study. The original system consists of 20 transmission lines and 14 buses. The slack bus is at bus 1. Four voltage-controlled buses are bus 2, 3, 6, and 8 and the remaining nine buses are of load bus type. The following modifications are made to the original system.

- a. Voltage magnitude at slack bus is 1.05 p.u.
- b. Voltage magnitudes for all voltage-controlled bus are 1.02 p.u.
- c. Maximum limits of reactive power generated at voltage-controlled bus are reduced by half.
- d. Reactive power demands of all load bus are doubled.

The base value for power is 100 MVA. SVC parameters,  $X_C$  and  $X_L$ , are assumed as 1.0 and 0.5 p.u. respectively. With the given values of SVC parameters and base power,  $Q_{SVC}^{min}$  and  $Q_{SVC}^{max}$  for this case study are -100 and 100 MVar. The limits of  $v^{min}$  and  $v^{max}$  are 0.95 and 1.05 p.u.

**Table 1. Detail of Case Study**

Case	Decision Variable	Number of SVC
1	-	-
2	$Q_{SVC}$	3
3	$V_{SVC}$	3
4	$Q_{SVC}$	5
5	$V_{SVC}$	5
6	$Q_{SVC}$	7
7	$V_{SVC}$	7

Note : 1)  $Q_{SVC}$  is SVC reactive power  
 2)  $V_{SVC}$  is voltage magnitude at SVC connection point  
 3) bus number is used as the decision variable to define location of SVC for cases 2 to 7.

For PSO parameters, the number of particles in swarm and maximum number of iterations are equal to 100 and 150. The values of PSO acceleration constant are 2.0 while the PSO inertia weight is linearly decreased from 0.9 in the first iteration to 0.4 in the final iteration.

Seven cases in Table 1 are investigated for comparative study. The system without SVC placement is set as case 1 to represent the base case of the system. The differences in cases 2 to 7 depend on the decision variable used to find the optimal sizes of SVC and the number of SVC given for optimal allocation.

**8. RESULTS AND DISCUSSIONS**

For the base case, the total active and reactive power losses of the network are 17.83 MW and 51.41 MVar. All bus voltages are shown in Figure 2. The maximum bus voltage of 1.05 p.u. is at slack bus while the minimum bus voltage of 0.8503 p.u. is found at bus 14. It is observed that voltages at buses 3 to 14 of the base case violate the lower limit of 0.95 p.u.

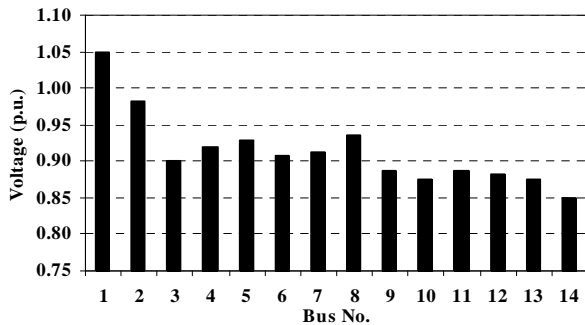


Fig. 2. Bus voltages in base case.

The optimal SVC placements for all cases, comprising bus numbers and the values of SVC reactive power, are summarized in Table 2. It should be noted that the optimal SVC reactive power of cases 2, 4, and 6 shown in Table 2 are directly provided by the optimal solutions of the proposed PSO-based technique. For cases 3, 5, and 7, the optimal solutions defined by the proposed technique are the magnitudes of SVC bus voltage. These voltages are used to calculate the optimal SVC reactive power as listed in Table 2 by power flow calculation including SVC and Eq.(4).

Considering the optimal SVC placement in cases 2 and 3, they are identical in both sites and sizes. For cases 4 and 5, their optimal installations identify the same best location for SVC with slight difference in the values of proper size for SVC at each location. The similar observations, as mentioned in cases 4 and 5, are also found when the optimal SVC allocation in case 6 is compared with that of case 7. These findings indicate that when the equal number of SVC is allowed for installation, whether  $Q_{SVC}$  or  $V_{SVC}$  is chosen to be the decision variable for searching optimal sizes of SVC, both of them provide almost the same choices for SVC placement.

The use of  $Q_{SVC}$  and  $V_{SVC}$  as the decision variable results in the differences of 1) the information of SVC required

for power flow problem and 2) power flow solution method to be implemented in the solution algorithm. When  $Q_{SVC}$  is a decision variable, the power flow calculation is performed by the conventional Newton-Raphson method and the data for operating limits of SVC reactive power is necessary. On the contrary, the parameters of SVC (see Section 2) must be provided and the power flow problem is solved by power flow solution including SVC when  $V_{SVC}$  is the decision variable.

Table 2. Optimal SVC placement for all cases by PSO

Bus No.	$Q_{SVC}$ (MVar)					
	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
5	-66.87	-66.87	-44.69	-44.74	-37.94	-38.10
7	-	-	-31.52	-31.30	-33.15	-32.98
10	-18.39	-18.39	-14.32	-14.38	-11.74	-11.88
11	-	-	-	-	-4.86	-4.81
12	-	-	-	-	-4.26	-4.20
13	-	-	-15.99	-15.99	-13.56	-13.63
14	-14.74	-14.74	-10.16	-10.28	-10.48	-10.39

Table 3. Loss and voltage for all cases by PSO

Case	$P_{loss}$ (MW)	$Q_{loss}$ (MVar)	$V_{min}$ (p.u.)	$V_{max}$ (p.u.)
1	17.83	51.41	0.8503	1.05
2	14.10	31.28	0.9652	1.05
3	14.10	31.28	0.9652	1.05
4	13.97	30.47	0.9665	1.05
5	13.97	30.46	0.9665	1.05
6	13.94	30.06	0.9667	1.05
7	13.94	30.05	0.9667	1.05

Note :  $P_{loss}$  = total system active power loss  
 $Q_{loss}$  = total system reactive power loss  
 $V_{min}$  = minimum voltage found in the system  
 $V_{max}$  = maximum voltage found in the system

All the values of optimal  $Q_{SVC}$  in Table 2 are less than zero. This indicates that SVC connected to each bus injects its reactive power to the network for reactive power compensation. The advantages of SVC are illustrated in Table 3. The reductions of system active and reactive power losses about 20% and 40% are presented by the optimal SVC placement. The values of minimum and maximum voltage found in the system also imply that all bus voltages are developed to stay within the specified limits. Loss reduction and voltage improvement are the evidences to support the benefits of optimal SVC placement for reactive power compensation.

For comparison purpose, the solution method based on GA has been developed for the same SVC allocation problem. Its optimal sites and sizes including other related results are provided in Tables 4 and 5. With

different locations of SVC placement and minimum bus voltages, the total MW loss for each case in Tables 3 and 5 are almost the same, indicating the existence of multiple solutions in this problem. However, GA takes 4 times as much computation time as PSO. This inferiority primarily originates from the lengthy processes required in reproduction, crossover and mutation in GA.

**Table 4. Optimal SVC placement for all cases by GA**

Bus No.	$Q_{SVC}$ (MVar)					
	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
4	-	-	-	-	-2.34	-2.12
5	-66.86	-66.85	-45.72	-44.80	-42.84	-43.07
7	-	-	-30.78	-31.21	-	-
9	-	-	-	-	-26.55	-26.95
10	-18.36	-18.42	-14.13	-14.38	-13.89	-13.54
11	-	-	-	-	-	-
12	-	-	-	-	-4.74	-4.82
13	-	-	-15.90	-16.02	-14.36	-14.18
14	-14.78	-14.76	-10.24	-10.28	-10.33	-9.87

**Table 5. Loss and voltage for all cases by GA**

Case	$P_{loss}$ (MW)	$Q_{loss}$ (MVar)	$V_{min}$ (p.u.)	$V_{max}$ (p.u.)
2	14.10	51.41	0.8503	1.05
3	14.10	31.28	0.9652	1.05
4	13.97	31.28	0.9652	1.05
5	13.97	30.47	0.9665	1.05
6	13.95	30.46	0.9665	1.05
7	13.95	30.06	0.9667	1.05

To clearly present the advantages of SVC in the view point of economic benefits, more information about energy loss cost and SVC installation cost should be calculated. The energy loss cost is the multiplication of active power loss, time duration and the value of per unit energy cost, while SVC installation cost is calculated by Eq.(20) given below.

$$IC_{SVC} = \sum_{m \in M} (aQ_{SVC,m}^3 + bQ_{SVC,m}^2 + cQ_{SVC,m}) \quad (20)$$

- where  $IC_{SVC}$  = SVC installation cost (\$)
- $m$  = bus number where SVC is located
- $M$  = set of buses for SVC placement
- $Q_{SVC,m}$  = reactive power of SVC at bus  $m$  (MVar)
- $a, b, c$  = cost coefficient

In this work, the time duration is based on one-year period and the per unit energy cost is 60 \$/MWh. The values of  $a$ ,  $b$ , and  $c$  in Eq.(20) are taken from [14] as

0.3, -305.1, and 127,380 respectively.

As seen in Tables 2 and 3, the optimal SVC placement and their related results in cases 2, 4, and 6 are mostly similar to those of cases 3, 5, and 7 respectively. For this reason, we can select only the results from cases 2, 4, and 6 to represent the economic benefits of SVC placement. The energy loss cost, the SVC installation cost, and the total cost (defined as the sum of energy loss cost and the installation cost) for cases 2, 4, and 6 are computed and expressed in Table 6.

**Table 6. Summary of cost for cases 1, 2, 4, and 6**

	Case 1	Case 2	Case 4	Case 6
Ecost (\$)	9,371,448	7,410,960	7,342,632	7,326,864
SVC cost (\$)	-	11,296,328	13,818,351	13,884,565
Total cost (\$)	9,371,448	18,707,288	21,160,983	21,211,429
RE (\$)	-	1,960,488	2,028,816	2,044,584
PBP (year)	-	5.76	6.81	6.79

- Note : Ecost = energy loss cost
- SVC cost = installation cost of SVC
- Total cost = sum of Ecost and SVC cost
- RE = reduction of energy loss cost
- PBP = payback period

It can be seen in Table 6 that the optimal installation of SVC can offer the reduction of energy loss cost. Although the energy loss cost after SVC placement is decreased, the total cost is greater. It is because the installation cost of SVC is relatively high compared with the benefit received from the reduction of energy loss cost. From a calculation of simple payback period, SVC placement takes about 5.8 years (for case 2) and 6.8 years (for cases 4 and 6) to recover its investment cost. However, as far as a trouble-free operation time of 15 years [15] and a lifetime of 30 years [16] are concerned, SVC is still worth economic justification.

## 9. CONCLUSION

A PSO-based optimization technique is presented in this paper to determine the optimal allocation of SVC in transmission systems for active power loss reduction. A case study is carried out with a modified IEEE 14-bus system to demonstrate the effectiveness of the proposed methodology and to compare the optimal SVC placement obtained by using different decision variables; reactive power of SVC and voltage magnitude at SVC connection point, to search for the optimal sizes of SVC reactive power.

The performance of the proposed technique is illustrated by the obtained optimal solutions which can provide the advantages of SVC for reactive power compensation while satisfying all the specified constraints. The test results reveal that the mostly similar strategies for SVC placement are identified whether reactive power of SVC or voltage at SVC bus is applied as the decision variable to find the optimal sizes of SVC. The difference between using these two variables is the information of SVC parameters required



for the solution algorithm.

In addition, the economic benefits of SVC are evaluated using the energy loss cost and the investment cost of SVC. It is observed that when the advantage from active power loss reduction is only considered, SVC seems to be so costly that it is not worthwhile, at least, in the short term. However, SVC can offer more advantages in other applications to the network (e.g. system security and loadability improvement, voltage stability enhancement, system reliability increase, generation cost reduction). Therefore, the economic benefits of SVC placement could be more attractive when such advantages are taken into account for the economic assessment of SVC placement.

**REFERENCES**

[1] Hingorani, N. G. and Gyugyi, L. 2000. *Understanding FACTS: Concept and Technology of Flexible AC Transmission Systems*. New York: IEEE Press.

[2] Zhang, X.P., Rehtanz, C. and Pal, B. 2006. *Flexible AC Transmission Systems: Modelling and control*. New York: Springer Berlin Heidelberg.

[3] Acha, E., Fuerte-Esquivel, C. R., Ambriz-Perez, H. and Angeles-Camacho, C. 2004. *FACTS; Modelling and Simulation in Power Networks*. Chichester: John Wiley & Sons Ltd.

[4] Goldberg, D.E. 1989. *Genetic Algorithms in Search Optimization and Machine Learning*. Reading: Addison-Wesley Publishing Company Inc.

[5] Glover, F. 1989. Tabu Search Part I. *ORSA J. Computing* 1(3): 190-206.

[6] Aarts, E. and Korst, J. 1989. *Simulated Annealing and Boltzmann Machine: a Stochastic Approach to Combinatorial Optimization and Neural Computing*. Chichester: John Wiley & Sons Ltd.

[7] Kennedy, J. and Eberhart, R. 1995. Particle swarm optimization. In *Proc. of IEEE International Conference on Neural Network*. Perth, Australia. 27 November-1 December. IEEE Press.

[8] Park, J.B., Lee, K.S., Shin, J.R. and Lee, K.Y. 2005. A particle swarm optimization for economic dispatch with nonsmooth cost functions. *IEEE Transactions on Power Systems* 20(1): 34-42.

[9] Ambriz-Perez, H., Acha, E. and Fuerte-Esquivel, C.R. 2000. Advanced SVC models for Newton-Raphson load flow and Newton optimal power flow. *IEEE Transactions on Power Systems* 15(1): 129-136.

[10] Miller, T. J. E. 1982. *Reactive Power Control in Electric Systems*. New York: John Wiley & Sons Inc.

[11] Grainger, J.J. and Stevenson, Jr. W.D. 1994. *Power System Analysis*. New York: McGraw-Hill Inc.

[12] Engelbrecht, A. P. 2007. *Computational Intelligence: An Introduction 2nd ed*. West Sussex: John Wiley & Sons Ltd.

[13] Pai, M.A. 2006. *Computer Techniques in Power System Analysis 2nd ed*. New Delhi: Tata McGraw-Hill.

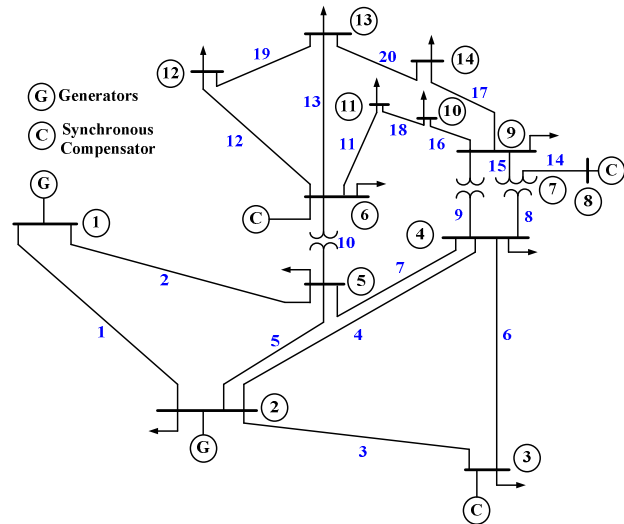
[14] Cai, L.J, Erlich, I. and Stamtis, G. 2004. Optimal choice and allocation of FACTS devices in deregulated electricity market using genetic algorithms. In *Proc. of IEEE PES Power Systems Conference and Exposition*. Essen, Germany. 10-13 October. IEEE Press.

[15] Cepek, M. and Krishnayya, C.P. 1998. Thyristor aging. In *Proc. of International Conference on Power System Technology*. Beijing, China. 18-21 August. IEEE Press.

[16] Gitizadeh, M. and Kalantar, M. 2008. A novel approach for optimum allocation of FACTS devices using multi-objective function. *Energy conversion and Management* 50(3): 682-690.

**APPENDIX**

This section provides data of the modified IEEE 14-bus test system which is the test system in the case study.



**Fig. A1. The IEEE 14-bus System**

**Table A1. Data of voltage-controlled buses in the modified IEEE 14-bus system**

Bus No.	Voltage magnitude (p.u.)	Reactive power limit	
		Min (MVar)	Max (MVar)
2	1.02	-40.0	25.0
3	1.02	0.0	20.0
6	1.02	-6.0	12.0
8	1.02	-6.0	12.0



**Table A2. Load data of the modified IEEE 14-bus system**

Bus No.	P (MW)	Q (MVAr)	Qc (MVAr)
1	-	-	-
2	21.7	25.4	-
3	94.2	38.0	-
4	47.8	-7.8	-
5	7.6	3.2	-
6	11.2	15.0	-
7	-	-	-
8	-	-	-
9	29.5	33.2	19.0
10	9.0	11.6	-
11	3.5	3.6	-
12	6.1	3.2	-
13	13.5	11.6	-
14	14.9	10.0	-

**Table A3. Line data**

Line No.	From bus	To bus	R (p.u.)	X (p.u.)	B/2 (p.u.)	Tr. Tap setting
1	1	2	0.01938	0.05917	0.02640	-
2	1	5	0.05403	0.22304	0.02460	-
3	2	3	0.04699	0.19797	0.02190	-
4	2	4	0.05811	0.17632	0.01870	-
5	2	5	0.05695	0.17388	0.01700	-
6	3	4	0.06701	0.17103	0.01730	-
7	4	5	0.01335	0.04211	0.00640	-
8	4	7	-	0.20912	-	0.978
9	4	9	-	0.55618	-	0.969
10	5	6	-	0.25202	-	0.932
11	6	11	0.09498	0.19890	-	-
12	6	12	0.12291	0.25581	-	-
13	6	13	0.06615	0.13027	-	-
14	7	8	-	0.17615	-	-
15	7	9	-	0.11001	-	-
16	9	10	0.03181	0.08450	-	-
17	9	14	0.12711	0.27038	-	-
18	10	11	0.08205	0.19207	-	-
19	12	13	0.22092	0.19988	-	-
20	13	14	0.17093	0.34802	-	-

