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A NEW TECHNIQUE TO IMPLEMENT SVC IN OPTIMAL POWER FLOW

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ABSTRACT

The objective of an Optimal Power Flow (OPF) algorithm is to find steady state operating point which minimizes generation cost loss etc. or maximizes social welfare, loadability etc. while maintaining an acceptable system performance in terms of limits on generators' real and reactive powers, line flow limits, output of various compensating devices etc. Traditionally, classical optimization methods were used to effectively solve OPF. But more recently due to incorporation of FACTS devices and deregulation of a power sector, the traditional concepts and practices of power systems are superimposed by an economic market management. So OPF have become complex. In recent years, Artificial Intelligence (AI) methods have emerged which can solve highly complex OPF problems. The purpose of this paper is to present a study of some optimization techniques used to solve OPF problems and a technique for optimal sizing and implementation of the SVC in optimal power flow. To show the effectiveness of the algorithm a IEEE 26 bus system has been used.

Keywords: FACTS devices, flexible A.C. transmission system, optimal power flow, static var compensator.

INTRODUCTION

The optimal power flow problem has been frequently solved using classical optimization methods. The OPF has been usually considered as the minimization of an objective function representing the generation cost and/or the transmission loss [1]. The constraints involved are the physical laws governing the power generation-transmission systems and the operating limitations of the equipment. Effective optimal power flow is limited by (i) the high dimensionality of power systems and (ii) the incomplete domain dependent knowledge of power system engineers. The first limitation is addressed by numerical optimization procedures based on successive linearization using the first and the second derivatives of objective functions and their constraints as the search directions or by linear programming solutions to imprecise models. The advantages of such methods are in their mathematical underpinnings, but disadvantages exist in the sensitivity to problem formulation, algorithm selection and usually converge to a local minimum. The second limitation, incomplete domain knowledge, precludes also the reliable use of expert systems where rule completeness is not possible.

PROBLEM FORMULATION

The standard OPF problem can be written in the following form [2],
Minimise *F(x)* (the objective function)
Subject to: (equality constraints)
$H_i(x) = 0$, i = 1, 2 , ...,n (inequality constraints)
$G_j(x) = 0$, j = 1, 2 , ..., m

Where x is the vector of the control variables that is those which can be varied by a control center operator (generated active and reactive powers, generation bus voltage magnitudes, transformers taps etc.);

The essence of the optimal power flow problem resides in reducing the objective function and simultaneously satisfying the load flow equations (equality constraints) without violating the inequality constraints

a. Objective function

The most commonly used objective in the OPF problem formulation is the minimization of the total cost of real power generation. The individual costs of each generating unit are assumed to be function, only, of active power generation and are represented by quadratic curves of second order. The objective function for the entire power system can then be written as the sum of the quadratic cost model at each generator.

$$F(x) = \sum_{i=0}^{n} \left(a_i + b_i P_i + c_i P_i^2\right) \tag{1}$$

where n is the number of generators including the slack bus. P_i is the generated active power at bus i. a_i, b_i and c_i are the unit costs curve for i^{th} generator.

b. Types of equality constraints

While minimizing the cost function, it's necessary to make sure that the generation still supplies the load demands plus losses in transmission lines. Usually the power flow equations are used as equality constraints.

$$\begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix} = \begin{bmatrix} P_i(V,\theta) & -\left(P_{g_i} - P_{d_i}\right) \\ Q_i(V,\theta) & -\left(Q_{g_i} - Q_{d_i}\right) \end{bmatrix} = 0 \tag{2}$$

where active and reactive power injection at bus i are defined in the following equation:

$$P_i(V,\theta) = \sum_{j=i}^{nbus} V_i V_j \left(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}\right) \quad ; \tag{3}$$

i = 2, …nbus

$$Q_i(V,\theta) = \sum_{j=i}^{nbus} V_i V_j \left(g_{ij} \sin\theta_{ij} + b_{ij} \cos\theta_{ij}\right);$$

i = npv+1,……. nbus. (4)

c. Types of inequality constraints

The inequality constraints of the OPF reflect the limits on physical devices in the power system as well as the limits created to ensure system security. The most usual types of inequality constraints are upper bus voltage limits at generations and load buses, lower bus voltage limits at load buses, Var limits at generation buses, maximum active power limits corresponding to lower limits at some generators and maximum line loading limits. The inequality constraints on the problem variables considered include:

- Upper and lower bounds on the active generations at generator buses $P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}$, *i = 1… n.*
- Upper and lower bounds on the reactive power generations at generator buses and reactive power injection at buses with VAR compensation Qgimin ≤ Qgi ≤ Qgimax, *i = 1, npv*
- Upper and lower bounds on the voltage magnitude at the all buses Vimin ≤ VI ≤ Vimax, *i = 1, nbus*.
- Upper and lower bounds on the bus voltage phase angles: $\theta_i^{min} \leq \theta_i \leq \theta_i^{max}$, *i = 1, nbus*.

It can be seen that the generalized objective function F is non-linear, the number of the equality and inequality constraints increase with the size of the power distribution systems. Applications of a conventional optimization technique such as the gradient-based algorithms to a large power distribution system with a very non-linear objective functions and great number of constraints are not good enough to solve this problem. Because it depends on the existence of the first and the second derivatives of the objective function and on the well enough computing of these derivatives in large search space.

ARTIFICIAL INTELLIGENCE (AI) METHODS

An artificial intelligence technique is the science of making an intelligent computer program. Even though excellent advancements have been made in classical methods, they suffer with the following disadvantages: In most cases, mathematical formulations have to be simplified to get the solutions because of the extremely limited capability to solve real-world large-scale power system problems. They are weak in handling qualitative constraints. They have poor convergence, may get stuck at local optimum, they can find only a single optimized solution in a single simulation run, they become too slow if number of variables are large and they are computationally expensive for solution of a large system.

Whereas, the major advantage of the Artificial intelligence methods is that they are relatively versatile for handling various qualitative constraints. Artificial intelligence methods can find multiple optimal solutions in single simulation run. So they are quite suitable in solving multiobjective optimization problems. In most cases, they can find the global optimum solution. The advantages of Genetic algorithms (GA) methods are: It only uses the values of the objective function and less likely to get trapped at a local optimum. Higher computational time is its disadvantage. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are the latest entry in the field of optimization. The main advantages of ACO are positive feedback for recovery of good solutions, distributed computation, which avoids premature convergence. It has been mainly used in finding the shortest route in transmission network, short term generation scheduling and optimal unit commitment. PSO can be used to solve complex optimization problems, which are non-linear, non-differentiable and multi-model. The main merits of PSO are its fast convergence speed and it can be realized simply for less parameters need adjusting. PSO has been mainly used to solve Bi-objective generation scheduling, optimal reactive power dispatch and to minimize total cost of power generation.

PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

Among the many AI techniques that have emerged off late and have been inspired by the nature, PSO is one of the latest and is amongst the best. After being proposed in mid 1990s, it has since then been utilized as an optimization tool in various applications, ranging from biological and medical applications to computer graphics and music composition.

Kennedy and Eberhart [3], considering the behavior of swarms in the nature, such as birds, fish, etc. developed the PSO algorithm. The PSO has particles driven from natural swarms with communications based on evolutionary computations. PSO combines self-experiences with social experiences. In this Algorithm, a candidate solution is presented as a particle. It uses a collection of flying particles (changing solutions) in a search area (current and possible solutions) as well as the movement towards a promising area in order to get to a global optimum.

PSO is initialized with a group of random particles and the searches for optima by updating generations [4]. In every iteration each particle is updated by following “two best” values. The first one is the best solution (fitness value) it has achieved so far. This value is called P_{best}. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is the global best called G_{best}. After finding the best values the particles update its velocity and position with the following equation:

$$V_i^{j+1} = W*V_i^j + C1*(P_{besti} - S_i^j) + C2*\text{rand2}*(G_{besti} - S_i^j) \quad (5)$$

$$S_i^{j+1} = S_i^{j+1} + V_i^{j+1} \quad (6)$$

$$W = W_{max} - \frac{Wmax - Wmin}{imax} * iter \quad (7)$$

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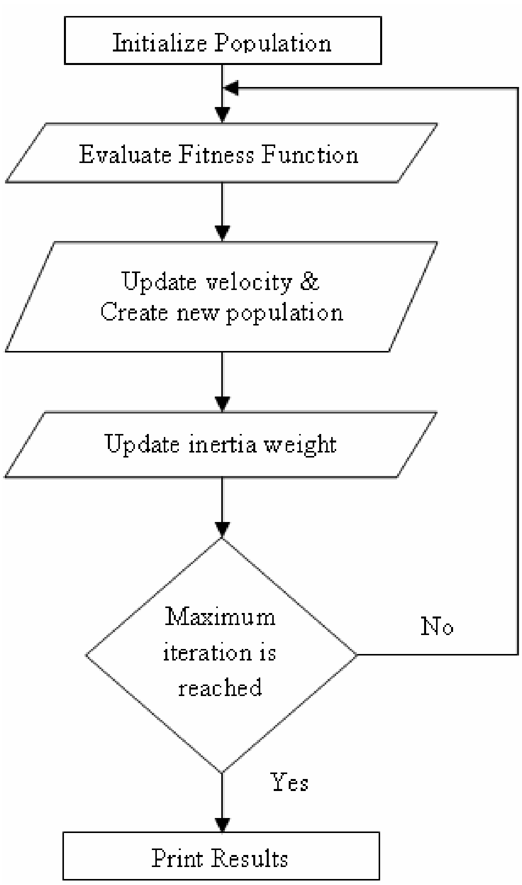
Where

V_i^j = Velocity of agent i at j_{th} iteration j +1
V_i^{j+1} = Velocity of agent i at (j +1) th iteration
W = The inertia weight
C1 = C2 = Weighting Factor
S_i^j = Current position of agent i at jth iteration
S_i^{j+1} = Current Position of agent i at (j+1) th iteration
imax = Maximum iteration number
iter = current iteration number
P_{besti} = P of agent i best
G_{besti} = G of the group best
W_{max} = Initial value of inertia weight
W_{min} = Final value of inertia weight

The velocity of the particle is modified by using (5) and the position is modified by using (6). The inertia weight factor is modified according to (7) to enable quick convergence. Implementation of an optimization problem of PSO is realized within the evolutionary process of a fitness function. The fitness function adopted is given as:

$$\textit{Fitness function} = \frac{1}{\textbf{objective + penalty}} \qquad (8)$$

where objective function is the generation cost and the penalty is the bus voltage angle. Penalty cost has been added to discourage solutions which violate the binding constraints. Finally, the penalty factor is tended to zero. The PSO algorithm to solve the optimal power flow with FACTS devices can be summarized as follows:



GENETIC ALGORITHM

Genetic algorithms are search algorithms based on the process of biological evolution. In genetic algorithms, the mechanics of natural selection and genetics are emulated artificially. The search for a global optimum to an optimization problem is conducted by moving from an old population of individuals to a new population using genetics-like operators [5, 6]. Each individual represents a candidate to the optimization solution. An individual is modeled as a fixed length of string of symbols, usually taken from the binary alphabet. An evaluation function, called fitness function, assigns a fitness value to each individual within the population. This fitness value is a measure for the quality of an individual. The basic optimization procedure involves nothing more than processing highly fit individuals in order to produce better individuals as the search progresses. A typical genetic algorithm cycle involves four major processes of fitness evaluation, selection, recombination and creation of a new population. The use of real valued representation in the GA is claimed by Wright to offer a number of advantages in numerical function optimization over binary encoding. Efficiency of the GA is increased as there is no need to convert chromosomes to the binary type; less memory is required as efficient floating-point internal computer representations can be used directly; there is no loss in precision by discretisation to binary or other values; and there is greater freedom to use different genetic operators. For the real valued representation, the k_{th} chromosome C_k can be defined as follows:

$$C_k = [P_{k1}, P_{k2}, \ldots, P_{kn}] \quad k = 1, 2, \ldots, m \qquad (9)$$

where *m* means population size and P_{ki} is the generation power of the *i*-th unit at *k*-th chromosome. Reproduction involves creation of new offspring from the mating of two selected parents or mating pairs. It is thought that the crossover operator is mainly responsible for the global search property of the GA. We used an arithmetic crossover operator that defines a linear combination of two chromosomes. Two chromosomes, selected randomly for crossover,

C_i^{gen} and C_j^{gen} may produce two offspring, C_i^{gen+1} and C_j^{gen+1}, which is a linear combination of their parent's i.e.

$$C_i^{gen+1} = \alpha.C_i^{gen} + (1-\alpha).C_j^{gen}$$

$$C_j^{gen+1} = (1-\alpha).C_i^{gen} + \alpha.C_j^{gen}$$

where α is a random number in range of [0, 1]. The mutation operator is used to inject new genetic material into the population and it is applied to each new structure individually. A given mutation involves randomly altering each gene with a small probability. We generate a random real value which makes a random change in the t_{th} element selected randomly of the chromosome. The objective function is used to provide a measure of how individuals have performed in the problem domain. In the case of a minimization problem, the most fit individuals will have the lowest value of the associated objective function. The fitness function is normally used to transform the objective function value into a measure of relative fitness. The fitness function is defined as

$$Fit(x) = g\,(f\,(x)) \tag{10}$$

where f(x) is the objective function, g transforms the value of the objective function to non-negative number. An elitist which GA search is used guarantees that the best solution so far obtained in the search is retained and used in the following generation and thereby ensuring no good solution already found can be lost in the search process.

Economic dispatch using genetic algorithm

The success of the genetic algorithm strongly depends on the problem mapping which involves the transformation of the problem solution to a chromosome representation and the design of the fitness function to assess the quality of a solution. Each chromosome within the population represents a candidate solution. A chromosome must represent a generation scheduling in order to solve the economic dispatch problem by using a genetic algorithm approach [7]. In the economic dispatch problem, the unit power output is used as the main decision variable, and each unit's loading range is represented by a real number. The representation takes care of the unit minimum and maximum loading limits since the real representation is made to cover only the values between the limits. The main objective of the economic dispatch is to minimize fuel costs while satisfying constraints such as the power balance equation. The fit individuals will have the lowest cost of the objective function of the economic dispatch problem. The fitness function is used to transform the cost function value into a measure of relative fitness. For the economic dispatch problem, the fitness function, Fit (P), may be expressed as

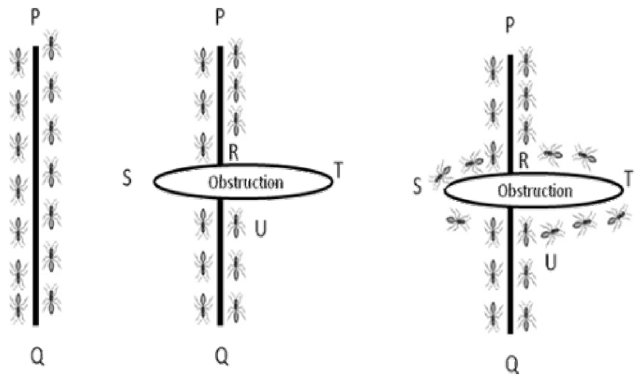
$$Fit(P) = \sum_{i=1}^{n} [g(a_i + b_i] P_i + c_i P_i^2) \tag{11}$$

In order to produce two offspring, an arithmetic crossover operator is used. After crossover is completed, mutation is performed. In the mutation step, a random real value makes a random change in the t^{th} element of the chromosome. After mutation, all constraints are checked whether violated or not. If the solution has at least one constraint violated, a new random real value is used for finding a new value of the t^{th} element of the chromosome. Then, the best solution so far obtained in the search is retained and used in the following generation. The genetic algorithm process repeats until the specified maximum number of generations is reached.

ANT COLONY OPTIMIZATION

Ant colony behavior

The ACSA imitates the behaviors of real ants [8]. As is well known, real ants are capable of finding the shortest path from food sources to the nest without using visual cues. Also, they are capable of adapting to changes in the environment, for example, finding a new shortest path once the old one is no longer feasible due to a new obstruction. Moreover, the ants manage to establish shortest paths through the medium that is called "pheromone." The pheromone is the material deposited by the ants, which serves as critical communication information among ants, thereby guiding the determination of the next movement. Any trail that is rich of pheromone will thus become the goal path. The process is illustrated by Figure-1.



(a) (b) (c)

Figure-1. Example of the real ant's behavior.

In Figure-1(a), the ants are moving from food source P to the nest Q on a straight line. Once an obstacle appears as shown in Figure-1(b), the path is cut off. The ants will not be able to follow the original trail in their movements. Under this situation, they have the same probability to turn right or left. But after some time the path RS will have more pheromones and all the ants will move in the path PRS. As the ants from R to reach T through S will reach quicker than that of the ants through T, i.e., RTU. Hence ant at U from Q will find pheromone a path USRP and will go through it, where Figure-1(c) depicts that the shorter path RSU will collect larger amount of pheromone than the longer path RTU. Therefore, more ants will be increasingly guided to move on the shorter path. Due to this autocatalytic process, very soon all ants will choose the shorter path. This behavior forms the fundamental paradigm of the ant colony search algorithm.

State transition rule and local/global updating rule

As illustrated in Figure-1, by the guidance of the pheromone intensity, the ants select preferable path. Finally, the favorite path rich of pheromone become the best tour, the solution to the problem. This concept develops the emergence of the ACSA method [9, 10]. At first, each ant is placed on a starting state. Each will build a full path, from the beginning to the end state, through the repetitive application of state transition rule. While constructing its tour, an ant also modifies the amount of pheromone on the visited path by applying the local updating rule. Once all ants have terminated their tour, the amount of pheromone on edge is modified again through

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the global updating rule. In other words, the pheromone updating rules are designed so that they tend to give more pheromone to paths which should be visited by ants. In the following, the state transition rule, the local updating rule and the global updating rule are briefly introduced.

State transition rule

The state transition rule used by the ant system, called a random-proportional rule, is given by the following, which gives the probability with which ant k in node i chooses to move to node j:

$$P_k(i,j) = \begin{cases} \dfrac{[\tau(i,j)][\eta(i,j)]^{\beta}}{\sum_{m \in J_k(i)}[\tau(i,m)][\eta(i,m)]^{\beta}} & ;\ \text{if } j \in J_k(i) \\ \text{Otherwise zero} \end{cases} \quad (12)$$

where τ is the pheromone which deposited on the edge between node i and node j , is the inverse of the edge distance, J_k (i) is the set of nodes that remain to be visited by ant k positioned on node i, and β is a parameter which determines the relative importance of pheromone versus distance. Equation (12) indicates that the state transition rule favors transitions toward nodes connected by shorter edges and with large amount of pheromone.

Local updating rule

While constructing its tour, each ant modifies the pheromone by the local updating rule. This can be written as τ_0 follows:

$$\tau(i,j) = (1-\rho)\tau(i,j) + \rho\tau_0 \quad (13)$$

Where τ_0 the initial pheromone is value, and ρ is a heuristically defined parameter. The local updating rule is intended to shuffle the search process. Hence the desirability of paths can be dynamically changed. The nodes visited earlier by a certain ant can be also explored later by other ants. The search space can be therefore extended. Furthermore, in so doing, ants will make a better use of pheromone information. Without local updating all ants would search in a narrow neighborhood of the best previous tour.

Global updating rule

When tours are completed, the global updating rule is applied to edges belonging to the best ant tour. This rule is intended to provide a greater amount of pheromone to shorter tours, which can be expressed as follows:

$$\tau(i,j) = (1-\sigma)\tau(i,j) + \sigma\delta^{-1} \quad (14)$$

Where δ is the distance of the globally best tour from the beginning of the trail, and $\sigma \epsilon [0,1]$ is the pheromone decay parameter. This rule is intended to make the search more directed; therefore the capability of finding the optimal solution can be enhanced through this rule in the problem solving process.

FACTS DEVICES

The flexible ac transmission systems are akin to high voltage dc and related thyristor developments, designed to overcome the limitations of the present mechanically controlled ac power transmission systems [11]. By using reliable, high speed power electronic controllers, the FACTS technology provides the utilities with five opportunities for increased efficiency.

- Greater control of power so that it flows on the prescribed transmission routes.
- Secure loading of transmission lines to levels nearer to their thermal limits.
- Greater ability to transfer between controlled areas.
- Prevention of cascading outages.
- Damping of power system oscillation.

The driving force for new and more cost effective FACTS equipment is the development of semiconductor devices. The most powerful are thyristors which can have a blocking ability of more than 10 kV and carry current up to 5 kA. However the GTO devices offer additional advantage for interrupting the current. These devices permit the use of forced commutated converters which are advantageous in building FACTS equipment with more advanced characteristics. The IGBT devices are used for converters in the lower rating ranges, mainly to be used in medium and low voltage network. The advantage of these devices is that they allow switching frequencies in the range up to 3 - 10 kHz.

The idea of FACTS is explained in Figure-2 which shows schematic diagram of an ac interconnection between two systems. The active power transmitted between the systems is defined by the given equation where U_1 and U_2 are the voltages at both ends of the transmission. X is the equivalent impedance of the transmission, and δ_1-δ_2 is the phase angle difference between both systems. From the equation it is evident that the transmitted power is influenced by three parameters: voltage, impedance and voltage angle difference. FACTS devices can influence one or more of these parameters as shown in Figure, and thereby influence power flow.

Figure-2 is a list of FACTS controllers [12] which have been realized or are still under development for application. They can be used for load flow control, voltage control and stability improvement in transmission system as well as for additional special applications.

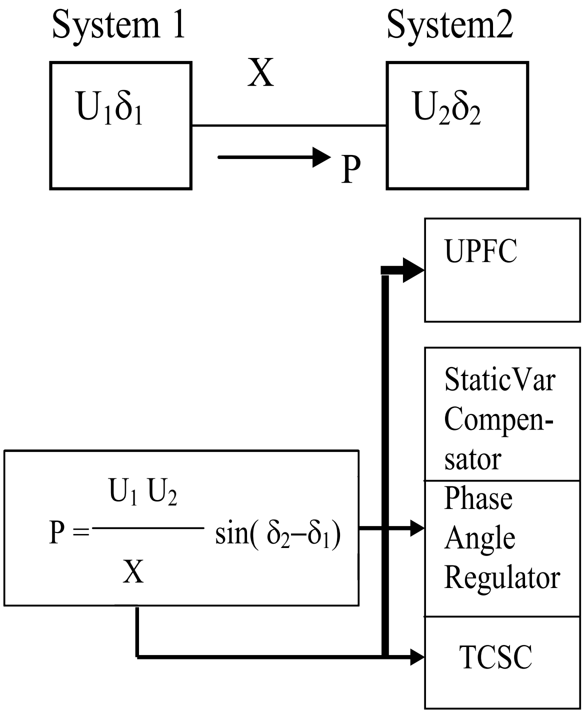

Figure-2. Representation of different controllers.

The advantage of FACTS is that combining a variety of different equipment can create different new members of the FACTS family. Advantages of FACTS controllers in ac system are shown in Table-1.

Table-1. Comparison of advantages of FACTS.

Device name	Load flow control	Voltage control	Transie nstability	Oscillation damping
SVC	*	***	*	**
TCSC	**	*	***	**
SSSC	***	**	***	**
UPFC	***	***	***	***

* small ** medium *** strong

As the first FACTS controller listed, SVC has already been in use for two decades with excellent operating experiences. The demand for SVC has increased continuously as systems become more heavily loaded and problems arise regarding voltage control. The second task for SVC to damp out power oscillations and to increase stability limit in long distance transmission system became important as new large transmission system were built.

APPLICATION STUDY

In the present paper, a new technique to implement the SVC in Optimal Power Flow [13,14,15] has been developed through MATLAB. It is tested using a 26-bus system. The Bus and Line Data of the system is presented in Tables 2 and 3. The system consists of 26 lines, 6 generators, 7 Tap-changing transformers, it can be seen that bus numbers 1, 2, 3, 4, 5 and 26 are generator buses and bus one is taken as reference bus others are taken as load buses. The initial angle at respective buses is assumed as zero degree. Accuracy is taken as = 0.01%.

Power flow solution by Newton-Raphson Method is applied. The voltage profile at various buses and the total generating cost is obtained as shown in Table-4. It can be easily observed that the bus voltage at bus no. 24 is found to be minimum and this may be the location to connect the FACT devices. Now aim is to evaluate the required reactive Mvar to be generated by FACTS devices.

A real power flow performance index method has been used to define the optimum location of FACTS devices. In our 26 bus system case bus 24 is most suitable bus to connect the SVC.

Modifications required in Load flow to include SVC

a) Shunt FACTS devices can be directly incorporated in load flow without modification of Jacobian.
b) The bus at which the SVC is connected has to be declared as generator bus with minimum and maximum reactive power limits.
c) After the load flow converges to a solution the reactive power to be generated at SVC bus will be known.
d) This reactive power corresponds to the rating of SVC.

To calculate the value of SVC, we declare the 24^{th} bus as a generator bus and apply Newton-Raphson method to get the optimal value of SVC at the 24^{th} bus. After load flow solution converges we get the reactive power to be generated at the 24^{th} bus that is the optimal rating of the SVC is to be connected at the same bus. It is shown in the Table-5.

After getting the optimal value of SVC at 24^{th} bus we again declare 24^{th} bus as load bus and connect the SVC at 24^{th} bus of the same rating. After connecting the SVC optimal power flow program in MATLAB is executed. After executing OPF, we get the improved voltage profile, improved voltage angle profile and reduced total generating cost as shown in Figures 3 and 4 and in Table-6.

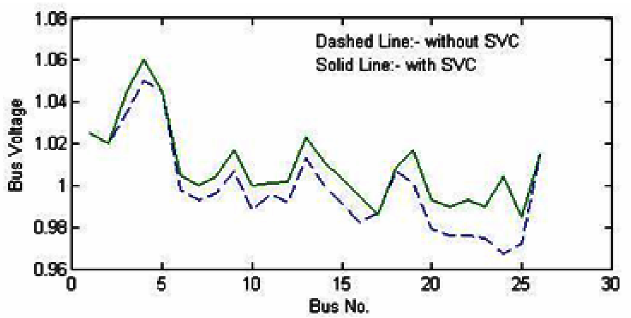

Figure-3. Comparison of the voltage profiles with and without the use of SVC.

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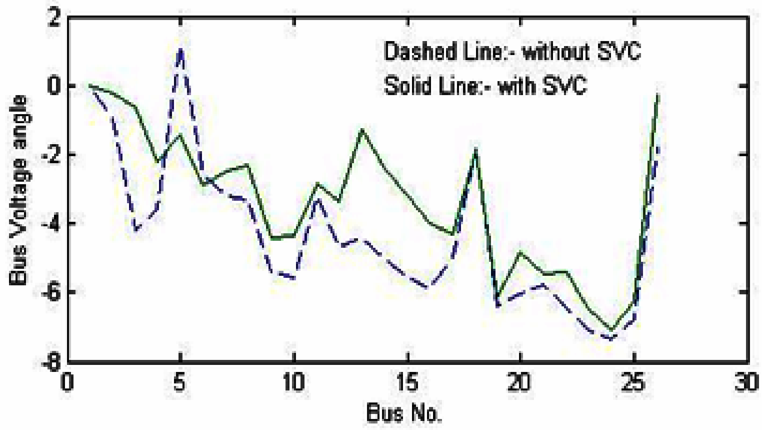

Figure-4. Comparison of the bus voltage angle variation with and without the use of SVC.

Table-2. Bus data.

Bus No	Voltage Mag.	Angle degree	Load		Generator			
			MW	Mvar	MW	Mvar	Qmin	Qmax
1	1.025	0.0	51	41	0	0	0	0
2	1.020	0.0	22	15	79	0	40	250
3	1.025	0.0	64	50	20	0	40	150
4	1.050	0.0	25	10	100	0	25	80
5	1.045	0.0	50	30	300	0	40	160
6	1.00	0.0	76	29	0	0	0	0
7	1.00	0.0	0	0	0	0	0	0
8	1.00	0.0	0	0	0	0	0	0
9	1.00	0.0	89	50	0	0	0	0
10	1.00	0.0	0	0	0	0	0	0
11	1.00	0.0	25	15	0	0	0	0
12	1.00	0.0	89	48	00	00	0	0
13	1.00	0.0	31	15	0	0	0	0
14	1.00	0.0	24	12	0	0	0	0
15	1.00	0.0	70	31	0	0	0	0
16	1.00	0.0	55	27	0	0	0	0
17	1.00	0.0	78	38	0	0	0	0
18	1.00	0.0	153	67	0	0	0	0
19	1.00	0.0	75	15	0	0	0	0
20	1.00	0.0	48	27	0	0	0	0
21	1.00	0.0	46	23	0	0	0	0
22	1.00	0.0	45	22	0	0	0	0
23	1.00	0.0	25	12	0	0	0	0
24	1.00	0.0	54	27	0	0	0	0
25	1.00	0.0	28	13	0	0	0	0
26	1.015	0.0	40	20	60	0	15	50

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Generator Operating Costs in \$/h, with P_i MW are as follows:

$C_1 = 240 + 7.0P_1 + 0.0070P_1^2$
$C_2 = 200 + 10.0P_2 + 0.0095P_2^2$
$C_3 = 220 + 8.5P_3 + 0.0090P_3^2$
$C_4 = 200 + 11.0P_4 + 0.0970P_4^2$
$C_5 = 220 + 10.5P_5 + 0.0080P_5^2$
$C_{26} = 190 + 12.0P_{26} + 0.0075P_{26}^2$

Generator real power limits are:

Generator	Minimum MW	Maximum MW
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

Table-3. Line data.

Bus No	Bus No	R p.u.	X p.u.	1/2 B p.u.	tr. tap at bus
1	2	0.00055	0.00480	0.03000	1
1	18	.00130	0.01150	0.06000	1
2	3	0.00146	0.05130	0.05000	0.96
2	7	0.01030	0.05860	0.01800	1
2	8	0.00740	0.03210	0.03900	1
2	13	0.00357	0.09670	0.02500	0.96
2	26	0.03230	0.19670	0.00000	1
3	13	0.00070	0.00548	0.00050	1.017
4	8	0.00080	0.02400	0.00010	1.050
4	12	0.00160	0.02070	0.01500	1.050
5	6	0.00690	0.03000	0.09900	1
6	7	0.00535	0.03060	0.00105	1
6	11	0.00970	0.05700	0.00010	1
6	18	0.00374	0.02220	0.00120	1
6	19	0.00350	0.06600	0.04500	0.95
6	21	0.00500	0.09000	0.02260	1
7	8	0.00120	0.00693	0.00010	1
7	9	0.00095	0.04290	0.02500	0.95
8	12	0.00200	0.01800	0.02000	1
9	10	0.00104	0.04930	0.00100	1
10	12	0.00247	0.01320	0.01000	1
10	19	0.05470	0.23600	0.00000	1
10	20	0.00660	0.01600	0.00100	1
10	22	0.00690	0.02980	0.00500	1
11	25	0.09600	0.27000	0.01000	1
11	26	0.01650	0.09700	0.00400	1

12	14	0.03270	0.08020	0.00000	1
12	15	0.01800	0.05980	0.00000	1
13	14	0.00460	0.02710	0.00100	1
13	15	0.01160	0.06100	0.00000	1
13	16	0.01793	0.08880	0.00100	1
14	15	0.00690	0.03820	0.00000	1
15	16	0.02090	0.05120	0.00000	1
16	17	0.09900	0.06000	0.00000	1
16	20	0.02390	0.05850	0.00000	1
17	18	0.00320	0.06000	0.03800	1
17	21	0.22900	0.44500	0.00000	1
19	23	0.03000	0.13100	0.00000	1
19	24	0.03000	0.12500	0.00200	1
19	25	0.11900	0.22490	0.00400	1
20	21	0.06570	0.15700	0.00000	1
20	22	0.01500	0.03660	0.00000	1
21	24	0.04760	0.15100	0.00000	1
22	23	0.02900	0.09900	0.00000	1
22	24	0.03100	0.08800	0.00000	1
23	25	0.09870	0.11680	0.00000	1

Table-4.

Bus No	Voltage Mag.	Angle degree	Load		Generator	
			MW	Mvar	MW	Mvar
1	1.025	0.000	51.000	41.000	719.634	230.539
2	1.020	-0.932	22.000	15.000	79.000	127.705
3	1.035	-4.216	64.000	50.000	20.000	64.704
4	1.050	-3.581	25.000	10.000	100.000	55.760
5	1.045	1.130	50.000	30.000	300.000	132.166
6	0.998	-2.564	76.000	29.000	0.000	0.000
7	0.993	-3.200	0.000	0.000	0.000	0.000
8	0.996	-3.296	0.000	0.000	0.000	0.000
9	1.007	-5.391	89.000	50.000	0.000	0.000
10	0.988	-5.558	0.000	0.000	0.000	0.000
11	0.996	-3.209	25.000	15.000	0.000	0.000
12	0.992	-4.690	89.000	48.000	0.000	0.000
13	1.013	-4.434	31.000	15.000	0.000	0.000
14	1.000	-5.042	24.000	12.000	0.000	0.000
15	0.991	-5.540	70.000	31.000	0.000	0.000
16	0.982	-5.884	55.000	27.000	0.000	0.000
17	0.987	-4.988	78.000	38.000	0.000	0.000
18	1.007	-1.864	153.000	67.000	0.000	0.000
19	1.001	-6.384	75.000	15.000	0.000	0.000
20	0.979	-6.023	48.000	27.000	0.000	0.000

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21	0.976	-5.775	46.000	23.000	0.000	0.000
22	0.976	-6.435	45.000	22.000	0.000	0.000
23	0.975	-7.083	25.000	12.000	0.000	0.000
24	0.967	-7.343	54.000	27.000	0.000	0.000
25	0.972	-6.770	28.000	13.000	0.000	0.000
26	1.015	-1.803	40.000	20.000	60.000	33.892
Total			1263.000	637.000	1278.634	644.765
	Total generation cost = 15449.22 $/h					

Table-5.

Bus No	Voltage Mag.	Angle degree	Load		Generator	
			MW	Mvar	MW	Mvar
1	1.025	0.000	51.000	41.000	719.163	219.500
2	1.020	-0.928	22.000	15.000	79.000	118.904
3	1.035	-4.194	64.000	50.000	20.000	56.469
4	1.050	-3.580	25.000	10.000	100.000	36.388
5	1.045	1.114	50.000	30.000	300.000	121.563
6	1.001	-2.608	76.000	29.000	0.000	0.000
7	0.995	-3.215	0.000	0.000	0.000	0.000
8	0.998	-3.304	0.000	0.000	0.000	0.000
9	1.011	-5.401	89.000	50.000	0.000	0.000
10	0.994	-5.575	0.000	0.000	0.000	0.000
11	0.999	-3.230	25.000	15.000	0.000	0.000
12	0.995	-4.692	89.000	48.000	0.000	0.000
13	1.014	-4.412	31.000	15.000	0.000	0.000
14	1.001	-5.022	24.000	12.000	0.000	0.000
15	0.993	-5.520	70.000	31.000	0.000	0.000
16	0.985	-5.873	55.000	27.000	0.000	0.000
17	0.989	-4.966	78.000	38.000	0.000	0.000
18	1.008	-1.875	153.000	67.000	0.000	0.000
19	1.013	-6.459	75.000	15.000	0.000	0.000
20	0.986	-6.051	48.000	27.000	0.000	0.000
21	0.988	-5.861	46.000	23.000	0.000	0.000
22	0.987	-6.505	45.000	22.000	0.000	0.000
23	0.985	-7.141	25.000	12.000	0.000	0.000
24	**1.000**	**-7.756**	**54.000**	**27.000**	**0.000**	**56.220**
25	0.982	-6.792	28.000	13.000	0.000	0.000
26	1.015	-1.801	40.000	20.000	60.000	30.995
Total			1263.000	637.000	1278.163	640.039

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Table-6.

Bus No	Voltage Mag.	Angle degree	Load		Generator	
			MW	Mvar	MW	Mvar
1	1.025	0.000	51.000	41.000	447.478	240.495
2	1.020	-0.200	22.000	15.000	447.478	29.931
3	1.045	-0.623	64.000	50.000	263.255	61.371
4	1.060	-2.193	25.000	10.000	137.594	62.266
5	1.045	-1.424	50.000	30.000	167.266	134.395
6	1.005	-2.910	76.000	29.000	0.000	0.000
7	1.000	-2.464	0.000	0.000	0.000	0.000
8	1.004	-2.345	0.000	0.000	0.000	0.000
9	1.017	-4.432	89.000	50.000	0.000	0.000
10	1.000	-4.372	0.000	0.000	0.000	0.000
11	1.001	-2.841	25.000	15.000	0.000	0.000
12	1.002	-3.346	89.000	48.000	0.000	0.000
13	1.023	-1.249	31.000	15.000	0.000	0.000
14	1.011	-2.440	24.000	12.000	0.000	0.000
15	1.003	-3.229	70.000	31.000	0.000	0.000
16	0.995	-3.998	55.000	27.000	0.000	0.000
17	0.986	-4.325	78.000	38.000	0.000	0.000
18	1.009	-1.890	153.000	67.000	0.000	0.000
19	1.017	-6.130	75.000	15.000	0.000	0.000
20	0.993	-4.819	48.000	27.000	0.000	0.000
21	0.990	-5.486	46.000	23.000	0.000	0.000
22	0.993	-5.424	45.000	22.000	0.000	0.000
23	0.990	-6.450	25.000	12.000	0.000	0.000
24	1.004	-7.079	54.000	27.000	0.000	0.000
25	0.985	-6.268	28.000	13.000	0.000	0.000
26	1.015	-0.301	40.000	20.000	86.436	25.050
Total	1263.000 637.000 1275.163 553.507					
	Total generation cost = 15438.07 $/h					

Thus it can also be seen that the total generation cost per hour comes down by 15449.22-15438.07= 11.15$/h as a result of the proposed SVC usage.

CONCLUSIONS

In this paper an attempt has been made to review various optimization methods used to solve OPF problems. A new powerful technique to implement FACTS devices is presented in this paper for the congestion management in the open power market. The merits of this method are that there is no requirement to modify the power mismatch equations to implement the FACTS devices. Application of this technique to Optimal Power Flow has been explored and tested. The simulation results show that this simple algorithm can give a good result using only simple modifications. This method can be used in any optimizations technique such as Particle Swarm Optimizations Technique, Genetic algorithms and ant Colony Search Algorithms.

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