CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents the literature survey related to different types of voltage stability analysis techniques, FACTS application to improve voltage stability, identification of location of FACTS using conventional methods, optimal location of FACTS device using PSO, GA and hybrid biologically inspired optimization techniques.

Ajjarapu and Lee (1998) presented comprehensive list of books, reports, workshops and technical papers related to voltage stability and security. Causes of voltage instability and different types of voltage instability are also reviewed (Lachs and Sutanto 1994). Different static methods and dynamic simulation with appropriate models for voltage stability assessments are proposed by Taylor (1994). Different techniques for voltage stability analysis are P-V analysis, Q-V analysis, Modal analysis and Time-Domain analysis.

2.2 VOLTAGE STABILITY ANALYSIS TECHNIQUES

Voltage instability has been responsible for several major network collapses. Some of the causes for occurrence of voltage instability (Kundur 1994) are:

1. Difference in transmission of reactive power under heavy loads.
2. High reactive power consumption at heavy loads.
3. Occurrence of contingencies.
4. Voltage sources are too far from load centers.
5. Unsuitable locations of FACTS controllers.
6. Poor coordination between multiple FACTS controllers.
7. Presence of constant power loads.
8. Reverse operation of ON load tap changer.

Bindeshwar Singh et al (2010), NERC (1991) and David and Hilt (2006) have mentioned several instances of severe voltage collapses. Alsberg (1996) mentions Western System Coordination Council disturbance of August 10, 1996. Mithulananthan et al (1998) talks about Sri Lankan power system disturbance of May 2, 1995. The consequences were severe in the WSCC system, approximately 7.5 million customers suffered from disruption in supply. In the Sri Lankan case, it took about an hour to bring the system back to normal, following a nationwide 30 minutes blackout.

2.2.1 Voltage Stability Analysis Using P-V Curve

In recent years, the increase in peak load demand and power transfers between utilities has resulted in concerns about system voltage security. Voltage collapse is considered responsible for several major disturbances, and research has mainly concentrated on the steady state aspects of voltage stability. A particular difficulty encountered in such research is that the Jacobian of a Newton-Raphson power flow becomes singular at the steady state voltage stability limit. In fact, this stability limit, also called the critical point, is often defined as the point where the power flow Jacobian is singular.

As a consequence, attempts at power flow solutions near the critical point are prone to divergence and error. (Ajjarapu and and Christy1992) demonstrated how singularity in the Jacobian can be avoided by slightly reformulating the power flow equations and applying a locally parameterized continuation technique. During the resulting "continuation power flow", the reformulated set of equations remains well-conditioned so that divergence and error due to a singular Jacobian are not encountered. Continuation power flow technique can be used to draw P-V curve. Intermediate results of the process were used to develop a voltage stability index and identify areas of the system most prone to voltage collapse, (Canizares et al 1992 , Perez Wei-Jen Lee 2006 and Zhang Yanping et al 2005).

2.2.2 Voltage Stability Analysis Using Q-V Curve

Q-V curve method is also used for voltage stability analysis (Chowdhury and Taylor 2000) and (Rao et al 1998). Q-V Curves are produced by running a series of load flow cases. They show the necessary amount of reactive power to achieve a specified voltage level. This method was developed to avoid difficulties in power flow program convergence of stressed cases close to the maximum loadability limit (Perez Wei-Jen Lee 2006). Lian et al (2009) proposed a novel analysis method using the P-V and the Q-V curves for voltage stability assessment of bulk power system

2.2.3 Voltage Stability Analysis Using Modal Analysis

Voltage stability analysis can be done using a modal analysis technique (Gao et al 1992, Kundur et al 1993). Modal analysis method computes, using a steady state system model, a specified number of the smallest eigenvalues and the associated eigenvectors of a reduced Jacobian matrix. The eigenvalues, each of which is associated with a mode of voltage/reactive power variation, provide a relative measure of proximity to voltage instability.

2.2.4 Voltage Stability Analysis Using Time Domain Analysis

Although different approaches have been proposed and employed for voltage collapse analysis till now, few have dealt with dynamics of this phenomenon in large interconnected power systems. Most of the voltage stability analysis methods that are applied to these networks are of static type. Little work has been published on dynamic voltage stability analysis of these systems, and the differences between the results of two approaches have been rarely analysed, the reason being the enormous time needed for modeling and computations of dynamic simulation. (Hasani and Parniani 2005), investigated the differences between static and dynamic techniques and combined these techniques to exploit the advantages of both approaches, (Morison et al 1993). For an accurate analysis of the dynamic voltage stability, the system model includes excitation systems, tap-changers, capacitors and power system stabilizers in addition to network equations. A parameter optimization technique with a modal performance measure is developed to determine optimal control parameters for dynamic voltage stability enhancement (Lee and Lee 1993).

A new methodology was proposed for online voltage stability assessment, consisting of two steps. Firstly, the time evolution of the power system operating state is modeled with the help of a forecasting-aided state estimator; secondly the voltage collapse point is determined through an extrapolation technique based on tangent vector behaviour (de Souza et al 2000).

2.2.5 Voltage Stability Indices Used for Voltage Stability Assessment

After some damaging blackouts, voltage stability and collapse have become a worldwide problem. An improved voltage stability index is developed, (Jia Hongjie et al 2004), which can give an accurate indication to power system voltage instability with considering the influence of load model (Thomas et al 1993).Voltage margin proximity index considering voltage limits, especially lower voltage limits is found, (Kataoka et al 2006), Voltage stability index L index can be used to identify the load bus which is prone to voltage instability (Kessel and Glavitsch 1986). The minimum singular value of the power flow jacobian matrix has been used as a static voltage stability index, indicating the distance between the studied operating point and the steady state voltage stability limit (Lof et al 1992, 1993). Emergency load shedding was used to avoid risk of voltage instability using indicators. The indicators were used for selecting the location and determining the amount of load to be shed, (Quoc Tuan et al 1994).

The determination of the voltage collapse operating margin is based on the evaluation of the proximity of the current operating point of a power system to the voltage collapse point. This proximity is calculated by tracing the path of the current operating point as one or more system parameters vary. Parameters under consideration include bus and area loads, line impedances and real/reactive generations. Voltage collapse margin uses a continuation technique for power flow, optimal power flow and governor power flow to perform the determination of the operating margin very efficiently, (Rajagopalan et al 1993). New data-processing method to estimate the proximity to voltage collapse is spurred by Vu et al (1999). This method (code-named SMART Device, for Stability Monitoring And Reference Tuning Device) employed only local measurements bus voltage and load current and calculated the strength of the transmission system relative to the bus.

Zhang Yanping et al (2005) introduced the concepts of load power deviation coefficient and the voltage deviation and compared the maximum load power and the voltage value corresponding to the P-V curve’s inflection point with the load power and the critical voltage value corresponding to the point when the eigenvalue of the system state matrix passes through the vertical axis. As a result of taking the inflection point of the P-V curve as the static voltage stability limit in the static voltage stability analysis. Deng Guiping et al (2009) proposed online tracking of voltage stability margin of the equivalent system considering distribution network

Contingency screening and ranking is one of the important components of on-line voltage stability assessment. This objective is to quickly and accurately select a short list of critical contingencies from a large list of potential contingencies and rank them according to their severity. Suitable preventive control actions can be implemented considering contingencies that are likely to affect the power system performance (Zhihong Jia et al 2000, Ejebe et al 1996, Musirin and Rahman 2002). Contingencies are ranked according to a performance index defined in terms of branch based voltage stability proximity indices, (Quintela and Castro 2002). Artificial neural network can be applied to evaluate the distance to the voltage collapse point using new method FSQV (Full Sum dQ/dV) (Andrade et al 2006).

Some of the techniques for prevention of voltage instability are:

1. Placement of series and shunt capacitors (Taegyun Kim et al 2009) and (Haifeng Liu et al 2009).

2. Installation of synchronous condensers.

3. Placement of FACTS controllers (Moghawemi and Faruque 2000).

4. Coordination of multiple FACTS controllers (Candelo et al 2006).

5. Under-voltage load shedding (Mozafari et al 2006).

6. Blocking of tap-changer under reverse operation.

7. Generation rescheduling.

2.3 IMPROVEMENT OF VOLTAGE STABILITY USING FACTS DEVICE

FACTS device was introduced by the Electric Power Research Institute (EPRI) in the late eighties. One of the major causes of voltage instability is the reactive power limits of the power systems. Several researchers have proposed solutions for this problem, by using suitable location of FACTS (Arthit Sode-Yome and Nadarajah Mithulananthan 2005). Hence, improving the systems reactive power handling capacity via FACTS device is a remedy for prevention of voltage instability and hence voltage collapse (Mathur and Varma 2002).

Power system network can be modified to alleviate voltage instability or collapse by adding reactive power sources i.e. shunt capacitors and/or FACTS devices at the appropriate locations. There are various types of FACTS devices available for this purpose, namely Static Var Compensator (SVC), Thyristor controlled series Capacitor (TCSC), Static Synchronous series compensator (SSSC), Static Synchronous Compensator (STATCOM), Unified Power Flow Controller (UPFC) and Interlink Power Flow Controller (IPFC) (Hingorani and Gyugyi 2000).

Applications of FACTS Device are:

1. Reactive power and voltage control (Jizhong Zhu et al 2010)
2. Increase thermal loading
3. Increase power transfer capability (Canizares and Faur1999)
4. Post contingency and Voltage control
5. Power flow balancing and control
6. Transient stability enhancement and Oscillation damping (Praing et al 2000)
7. Voltage stability enhancement (Kazemi et al 2006)
8. Sub Synchronous Resonance (SSR) elimination

2.3.1 Identification of Location of FACTS Using Conventional Methods

The effects of FACTS controllers—SVC, TCSC, STATCOM, SSSC and UPFC—on voltage stability can be studied. Natesan and Radman (2004), Bekri and Fellah (2010) have used Continuation Power Flow (CPF) through Power System Analysis Toolbox (PSAT), with accurate model of these controllers and obtained the optimal location of these controllers. They found that these controllers significantly enhance the voltage profile and thus the loadability margin of power systems. Milano (2005) has discussed in great detail the Power System Analysis Toolbox (PSAT).

Modal analysis technique is used to identify system areas prone to voltage instability as well as to determine the most effective locations for placement of FACTS controllers by Perez et al (2000), Sarmiento et al(2004), Sheikhi et al (2003), Jafari and Afsharnia (2007).

Gotham and Heydt (2005) presented power flow control and power flow studies for power systems with FACTS devices. The modelling of FACTS devices for power flow studies and the role of that modelling in the study of FACTS devices for power flow control have been discussed in Enrique Acha et al (2004), Sameh Kamel Mena Kodsi and Claudio (2003). Pourbeik et al (2007) presented a description of a comprehensive study to evaluate various reactive power compensation strategies for dealing with potential voltage stability issues in the Tucson Electric Power Company 138 kV electrical network.

Abdelsalam et al (2004) proposed an algorithm based on the steady state injection model of UPFC, a continuation power flow and an optimal power flow to find the best location of UPFC in order to minimize the generation cost function and the investment on the UPFC device. Kowsalya, et al (2008) examined the voltage space of the system with respect to the "centroid" of the system voltage space and identified the loadability of buses and ranked them accordingly. Their algorithm minimized the voltage stability index of all the load buses to improve the static voltage stability margin.

Larki et al (2009) presented a new approach for identification of optimal locations of STATCOM and SVC. Contingencies ranking were performed with continuation power flow method. Karami et al (2009) examined optimal location, appropriate size and setting of SVC and TCSC using power flow results. Yorino et al (2003) proposed a new formulation for reactive power planning problem including the allocation of SVC and TCSC FACTS devices. Their objective was to minimize the sum of the installation costs and the operating costs, which include the expected costs for voltage collapse, the emergency control costs for load shedding. The expected voltage collapse cost was calculated as a function of the load margin.

2.4 OPTIMAL LOCATION OF FACTS DEVICE USING BIOLOGICALLY INSPIRED OPTIMIZATION TECHNIQUES

Biologically inspired optimization techniques can be used to solve multi-objective optimization problem efficiently and effectively. Patrick Mills et al (2004) has enumerated and discussed several biologically inspired optimization techniques such as Genetic algorithms (GA), Guided Local Search, Tabu Search, Variable Neighbourhood Search, Iterated Local Search, Simulated Annealing, Greedy Randomized Adaptive Search Procedure, Memetic Algorithms, Scatter Search, Ant Colony Optimization, Particle Swarm Optimization (PSO) and Shuffled Frog Leaping algorithm. Holland (1975) has discussed in detail Genetic Algorithms while Eberhart and Kennedy (1995) has discussed in detail Particle Swarm Optimization.

2.4.1 Particle Swarm Optimization

PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995. PSO is an optimization tool, provides a population based search procedure in which individuals called particles change their position (state) 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 according to the experience of a neighbouring particle, making use of the best position encountered by itself and its neighbour.

The technique is based on the food-searching behaviour of birds with help from the global level of information to determine the birds' direction. The global and local best positions are computed at each iteration and the output is the new direction of search. Once this direction is detected, it is followed by the cluster of birds.

PSO uses a number of agents (particles) that constitute a swarm, moving around in the search space looking for the best solution. Each particle is treated as a point in a N-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles. Each particle keeps track of its coordinates in the solution space which is associated with the best solution (fitness) that is achieved so far by that particle. This value is called personal best, P_{best}. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called G_{best}. The particle swarm optimization (PSO) was shown to converge rapidly during the initial stages of a global search, but around global optimum, the search process would become very slow (Sumathi and Surekha 2010).

Similar to other population-based optimization methods such as genetic algorithms, the particle swarm algorithm starts with random initialization of a population of individuals (particles) in the search space. However, unlike in other evolutionary optimization methods, in PSO there is no direct recombination of genetic material between individuals during the search. This method is becoming very popular because of its simplicity of implementation and ability to quickly converge to a reasonably good solution.

2.4.1.1 Mathematical Model of PSO

The swarm of particles initialized with a population of random candidate solutions move through the d-dimension problem space to search new solutions. The fitness, f, can be calculated using Equation (3.22). Each particle has a position and a velocity. After every iteration, the best position among the swarm is stored. Velocity and position of each particle in the swarm are updated after each iteration, using Equations (2.1)-(2.3), (Sundareswaran et al 2010). The basic concept of PSO lies in accelerating each particle toward its P_{best} and the G_{best} locations, with a random weighted acceleration at each time step as shown in Figure 2.1.

$$v_i^{k+1} = w_i\, v_i^k + c_1 \times rand_1 \times \left(P_{best\,i} - s_i^k\right) + c_2 \times rand_2 \times \left(G_{best\,i} - s_i^k\right) \quad (2.1)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (2.2)$$

$$w = w_{max} - \frac{w_{max} - w_{min}}{iterw_{max}} \times iter \quad (2.3)$$

where

V_i^k: Velocity of i^{th} particle at k^{th} iteration;

V_i^{k+1}: Velocity of i^{th} particle at $(k+1)^{th}$ iteration

S_i^k: Current position of particle i at k^{th} iteration

S_i^{k+1}: Current position of particle i at $(k+1)^{th}$ iteration

$P_{best\,i}$: Best position of i^{th} particle

$G_{best\,i}$: Best position among the particles (group best)

c_1: Coefficient of the self-recognition component,

c_2: Coefficient of the social component

$c_1 + c_2 = 4$

$rand_1$ and $rand_2$ are the random numbers usually chosen between [0, 1]

w: Inertia weight,

w_{max}: Initial value of inertia weight;

w_{min}: Final value of inertia weight;

iter: Current iteration number;

$iterw_{max}$: Maximum iteration number

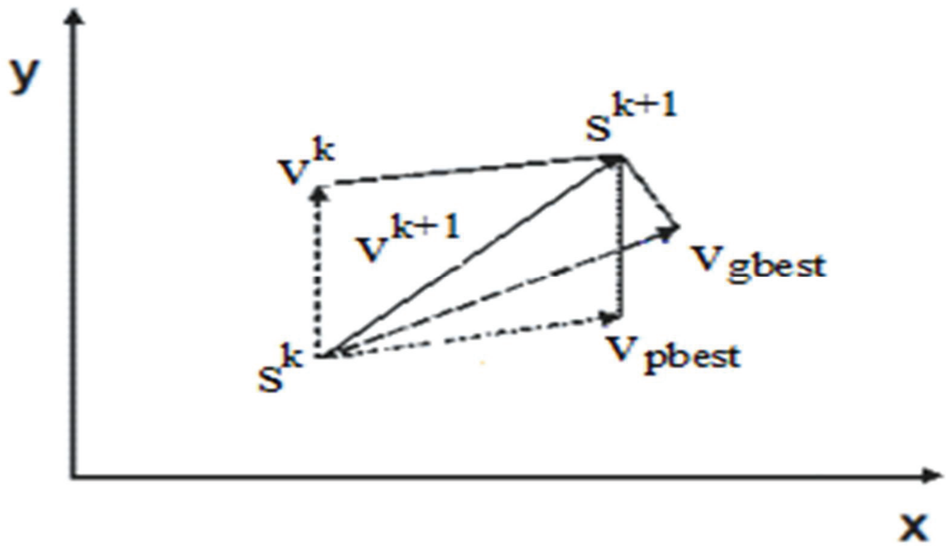

Figure 2.1 Search path of PSO

2.4.1.2 Parameters and Tuning of Parameters in PSO

Number of Particles: The number of particles is a very important factor to be considered. For most of the practical applications a best choice of the number of particles is typically in the range between 20 and 40. Usually 10 particles are a large number sufficient enough to get best results. In case of difficult problems, the choice can be 100 or 200 particles also.

Inertia Weight: The inertia weight plays a very important role in the convergence behavior of the PSO algorithm. The inertia weight is employed to control the impact of the previous history of velocities on the current one. Usually the best choice of the inertia weight is around 1.2, and as the algorithm progresses this value is gradually decreased to 0.

Learning Factors: The parameters c_1 and c_2, coefficient of self-recognition and social components, are not much critical for the convergence of PSO. Fine tuning of these learning vectors aids in faster convergence and alleviation of local minima. Usually the choice for these parameters is, $c_1 = c_2 = 2$, but some experiment results indicate that $c_1 = c_2 = 1.49$ might provide even better results. Recent papers report that it might be even better to choose a larger self-recognition component, c_1, than the social component, c_2, such that it satisfies the condition $c_1+c_2 = 4$.

Range and Dimension of Particles: The particle dimension and range is determined based on the problem to be optimized. Various ranges can be chosen for different dimension of particles.

Velocity Max: The maximum change one particle can take during one iteration is defined as the maximum velocity and denoted as Velocity max. Usually the range of particles is set as the maximum velocity. For instance, if a particle belongs to the range between -5 and 5, then the maximum velocity is 10.

Stopping Condition: The stopping condition depends on any one of the following criteria:

- The process can be terminated after a maximum number of iteration is reached.

- The process may be terminated when the error between the obtained objective function value and the best fitness value is less than a pre-fixed anticipated threshold.

2.4.1.3 Proposed Algorithm for PSO

The proposed algorithm for the optimal placement of SVC device using PSO is given below:

Step 1 : Initialize velocity, P_{best}, G_{best}, number of particles and maximum iteration.

Step 2 : For each particle, initialize SVC size and location of SVC.

Step 3 : Check whether maximum iteration is reached, if yes then obtain the optimum location and rating of SVC.

Step 4 : Run power flow program and compute objective function.

Step 5 : For each particle, determine and store P_{best}

Step 6 : For each particle, determine and store G_{best}

Step 7 : Update velocity and position using Equations (2.1)-(2.3).

Step 8 : If feasibility solution is obtained then go to step 3. Otherwise relocate particle to feasible position of search space.

2.4.1.4 Proposed Flowchart for PSO

The proposed flowchart for optimal location and rating of SVC device using PSO is shown in Figure 2.2.

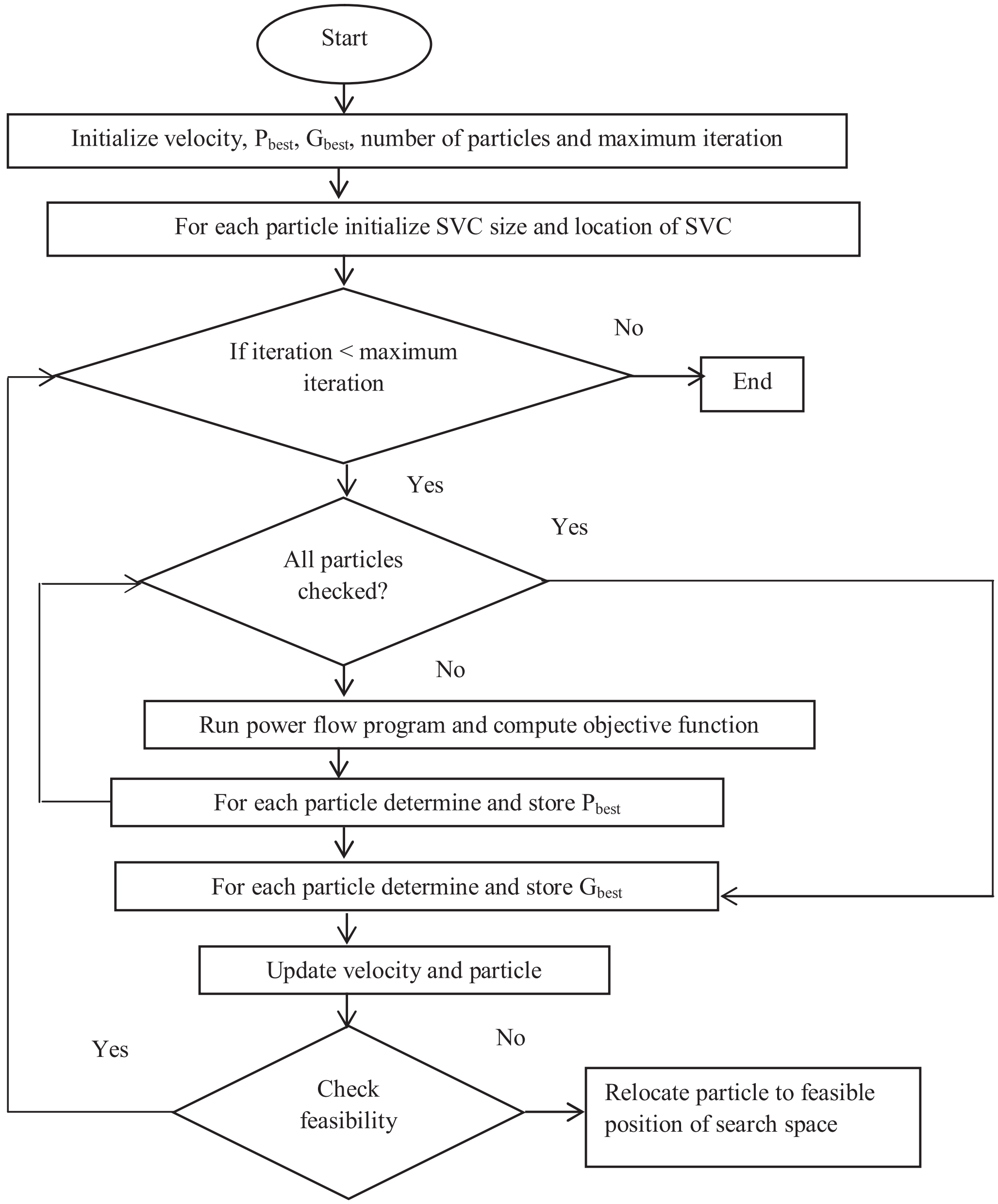

Figure 2.2 Flow chart for optimal location of SVC using PSO

2.4.1.5 Optimal Location of FACTS Device Using PSO

Saravanan et al (2005) applied PSO technique for optimal location of FACTS devices considering system loadability and cost of installation.

They were able to find maximum system loadability and minimum cost of installation of FACTS devices for single type and multi type FACTS.

Farsangi et al (2006) also used the PSO algorithm, which is used for planning SVC in a large scale power system. To enhance voltage stability, the planning problem was formulated as a multi-objective optimization problem for maximizing fuzzy performance indices. The multi-objective var planning problem in a large-scale power system was solved by the fuzzy PSO with very encouraging results, and the results are compared with those obtained by GA.

Rashed et al (2007) investigated the application of GA and PSO techniques for finding out the optimal number, the optimal locations, and the optimal parameter settings of multiple TCSC devices to achieve a maximum system loadability in the system with minimum installation cost of these device.

Shaheen et al (2008) suggested an approach to find out the optimal placement and the optimal parameters setting of UPFC for enhancing power system security under single contingencies. Contingency analysis and ranking process were performed to determine the severest line tripping contingencies; GA and PSO techniques were used to find out the optimal location and the optimal parameters setting of UPFC corresponding to the determined contingencies scenarios.

Sundareswaran et al (2010) investigated optimal locations for 3 SVC's in an IEEE 30 bus system using PSO. Das et al (2009) determined the location and amount of distributed FACTS compensation using PSO. Esmin et al (2005) presented PSO as a tool for loss reduction study. The study was carried out in two steps. First, by using the tangent vector technique, the critical area of the power system was identified under the point of view of voltage instability. Second, once this area was identified, the PSO technique calculated the amount of shunt reactive power compensation that takes place in each bus. Dib et al (2006) proposed a new solution technique for finding the optimum location and sizing of the shunt compensation devices in transmission system using PSO.

Guanglin Cai et al (2007) presented a modified particle swarm optimization method to realize optimal reactive power dispatch considering voltage stability improvement. The objective was to minimize the real power losses and control number and maximize voltage stability margin. The mutation was incorporated into the PSO. Hirotaka Yoshida et al (2001) presented PSO for reactive power and voltage control considering voltage security assessment. The method considers voltage security using a continuation power flow and a contingency analysis technique. The feasibility of the proposed method was demonstrated and compared with reactive tabu search.

Leeton et al (2010) described optimal power flow based on PSO in which the power transmission loss function was used as the problem objective. Sailaja Kumari et al (2007) investigated the performance of population based search algorithms (GA and PSO) when applied to Optimal Power Flow (OPF) including SVC and TCSC devices. Different objective functions that include fuel cost minimization, system power loss minimization, voltage stability enhancement (L-index minimization), power loss minimization with SVC device and power loss minimization with combined application of SVC and TCSC devices have been considered.

del Valle et al (2006) considered voltage deviation constraint at each bus and obtained optimal STATCOM sizing and placement using particle swarm optimization. Results from the illustrative example showed that the PSO was able to find the best size and location solution.

Nireekshana et al (2007) presented incorporation of unified power flow controller model for optimal placement using particle swam optimization technique. The voltage stability index was used to find location of the UPFC in the network. By comparing the results, it was observed that PSO was more effective than GA in terms of fitness function.

Benabid et al (2009) presented optimal location and size of SVC and TCSC for multi-objective static voltage stability enhancement. The optimal location and size of SVC and TCSC devices have been found to maximize the Static Voltage Stability Margin (SVSM), reduce the power losses and minimize load voltage deviation. The problem was formulated as a mixed discreet-continuous multi-objective optimization problem. A Non-dominated Sorting Particle Swarm Optimization (NSPSO) was used to solve multi-objective optimization problem.

Abdelaziz Laifa and Mohamed Boudour (2009), Ya-Chin Chang et al (2012) presented optimal location of SVC for voltage security enhancement using MOPSO. A Multi-Objective Particle Swarm Optimization (MOPSO) was used to solve a mixed continuous-discrete multi-objective optimization problem in order to find optimal location of SVC. The optimal location of SVC was used in order to improve the voltage stability margin, minimize load voltage deviation and reduce power losses under single line contingencies. A contingency analysis has been examined to determine the critical outages with respect to voltage security in order to evaluate their effect on the location analysis. The voltage stability was considerably enhanced in both normal state and critical contingencies.

Nasr Azadani et al (2009) found optimal placement of multiple STATCOM for voltage stability margin enhancement using PSO. The approach was based on the simultaneous application of PSO and Continuation Power flow (CPF). The system loadability, bus voltage profile improvement, the power system loss reduction and size of device were employed as the measure of power system performance in optimization algorithm. Goh et al (2007) investigated mathematically-complex voltage collapse problems using PSO and DE algorithms. Voltage collapse point obtained by both the PSO and DE algorithms was same as obtained using CPF technique.

2.4.2 Genetic Algorithm

GA was introduced by Holland (1975) and imitates basic principles of nature formulated by Darwin and Mendel. GA is an evolutionary computing method in the area of artificial intelligence. It is a stochastic global search and optimization method that is based on concepts from natural genetics and the Darwinian survival-of-the-fittest code. GA is a population based search and optimization technique. It is an interactive optimization procedure. Instead of working with a single solution in each iteration, a GA works with a number of solutions. Genetics is usually used to reach a near global optimum solution. In each iteration of GA, a new set of string (i.e. chromosomes) with improved fitness is produced using genetic operators (i.e. selection crossover and mutation). Main components of GA Algorithm are initialization, selection, crossover, mutation and termination, (Narmatha Banu and Devaraj 2008).

2.4.2.1 Various Operations of GA

Holland proposed GA as a heuristic method based on survival of the fittest. GA is a search algorithm that simulates Darwinian evolutionary principles, generating a population of feasible solutions to the problem and then manipulating those solutions, using genetic operations. The solutions are typically represented as finite sequences drawn from a finite alphabet of characters. Through selection, crossover and mutation operations, better solutions are generated out of current population of potential solutions. This process continues until an acceptable solution is found. In a genetic algorithm, the problem is either encoded or used directly in a series of bit strings that are manipulated by the algorithm. Most commercial solver problems are based on genetic algorithms, (Baghaee et al 2008, Sivanandam and Deepa 2008)

Genes: Genes are the basic instructions for building a Generic Algorithms. A chromosome is a sequence of genes. Genes describe a possible solution to a problem, without actually being the best solution. A gene is a bit string of arbitrary lengths. Representation of a Gene is shown in Figure 2.3.

1 0 1 0	1 0 1 1	1 1 1 0	0 1 0 11
↑	↑	↑	↑
Gene 1	Gene 2	Gene 3	Gene 4

Figure 2.3 Representation of a gene

Fitness: The fitness of an individual in a genetic algorithm is the value of an objective function for its phenotype. For calculating fitness, the chromosome has to be first decoded and the objective function has to be evaluated. The fitness not only indicates how good the solution is, but also corresponds to how close the chromosome is to the optimal one.

Population: A population is a collection of individuals. It consists of a number of individuals being tested, the phenotype parameters defining the individuals and some information about search space. The two important aspects of population are initial population generation and population size. Figure 2.4 shows the representation of population.

Population	Chromosome 1	1 1 1 0 0 0 1 0
	Chromosome 2	0 1 1 1 1 0 1 1
	Chromosome 3	1 0 1 0 1 0 1 0
	Chromosome 4	1 1 0 0 1 1 0 0

Figure 2.4 Representation of population

Encoding: Encoding is a process of representing individual genes. The process can be performed using bits, numbers, trees, arrays, lists or any other objects. The encoding depends mainly on the nature of the problem. It includes binary encoding, octal encoding, hexadecimal encoding, permutation encoding, value encoding and tree encoding.

Breeding: The breeding process is the heart of the genetic algorithm. It creates new and hopefully fitter individuals. The breeding cycle consists of three steps:

a. Selecting parents.

b. Crossing the parents to create new individuals (offspring or children).

c. Replacing old individuals in the population with the new ones.

Parent Selection: The better fitness values among the population are selected as the parents to produce a better generation. This fittest test is accomplished by adopting a selection scheme in which higher fitness individuals are being selected for contributing offspring in the next generation. Many selection schemes such as Roulette Wheel, Random, Rank, Tournament and Boltzmann selection schemes are available.

Reproduction: Reproduction is based on the principle of better fitness survival. It is an operator that obtains a fixed copies of number of solutions according to their fitness value. If the score increases, the number of copies increases too. A score value is associated to a solution relying on its distance from the optimal solution (closer distances to the optimal solution mean higher scores).

Crossover: The objective of crossover operator is to produce new individuals that are different from their parents but inherit their parents' genetic material. A selected chromosome is divided into two parts and recombining with another selected chromosome, which is also divided at the same crossover point. Many crossover schemes such as single point, two point, multipoint and uniform crossover are available.

Crossover Probability: The basic parameter in crossover technique is the crossover probability (Pc). Crossover probability is a parameter to describe how often crossover will be performed. If there is no crossover, offspring are exact copies of parents. If there is crossover, offspring are made from parts of both parent's chromosome. If crossover probability is 100%, then all offspring are made by crossover. If it is 0%, whole new generation is made from exact copies of chromosomes from old population.

Mutation: Mutation is used to avoid premature convergence of the population (which may cause convergence to a local, rather than global, optimum) and to fine-tune the solutions. The mutation operator is defined by a random bit value change in a chosen string with a low probability of such change.

Mutation Probability: The important parameter in the mutation technique is the mutation probability (Pm). The mutation probability decides how often parts of chromosome will be mutated. If there is no mutation, offspring are generated immediately after crossover (or directly copied) without any change. If mutation is performed, one or more parts of a chromosome are changed. If mutation probability is 100%, whole chromosome is changed, if it is 0%, nothing is changed. Mutation generally prevents the GA from falling into local extremes. Mutation should not occur very often, because then GA will change to random search.

Termination: The various stopping conditions are listed as follows:

- **Maximum generations–**The genetic algorithm stops when the specified number of generations has evolved.
- **Elapsed time–**The genetic process will end when a specified time has elapsed.
- **No change in fitness–**The genetic process will end if there is no change to the population's best fitness for a specified number of generations.
- **Stall generations**–The algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length stall generations.
- **Stall time limit**–The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.

2.4.2.2 Proposed Algorithm for GA

The proposed algorithm for the optimal placement of SVC device using GA is given below:

Step 1 : Create an initial population

Step 2 : Run power flow program

Step 3 : Evaluate fitness value of all the individuals.

Step 4 : Select a new population from the old population based on the fitness of the individuals as given by the evaluation function.

Step 5 : Apply genetic operators (mutation and crossover) to members of the population to create new solutions.

Step 6 : Evaluate the fitness value of new chromosomes and insert them into the population.

Step 7 : If the maximum iteration is reached, stop and return the best individual, if not, go to 4.

2.4.2.3 Proposed Flowchart for GA

The proposed flowchart for optimal location and rating of SVC device using GA is shown in Figure 2.5.

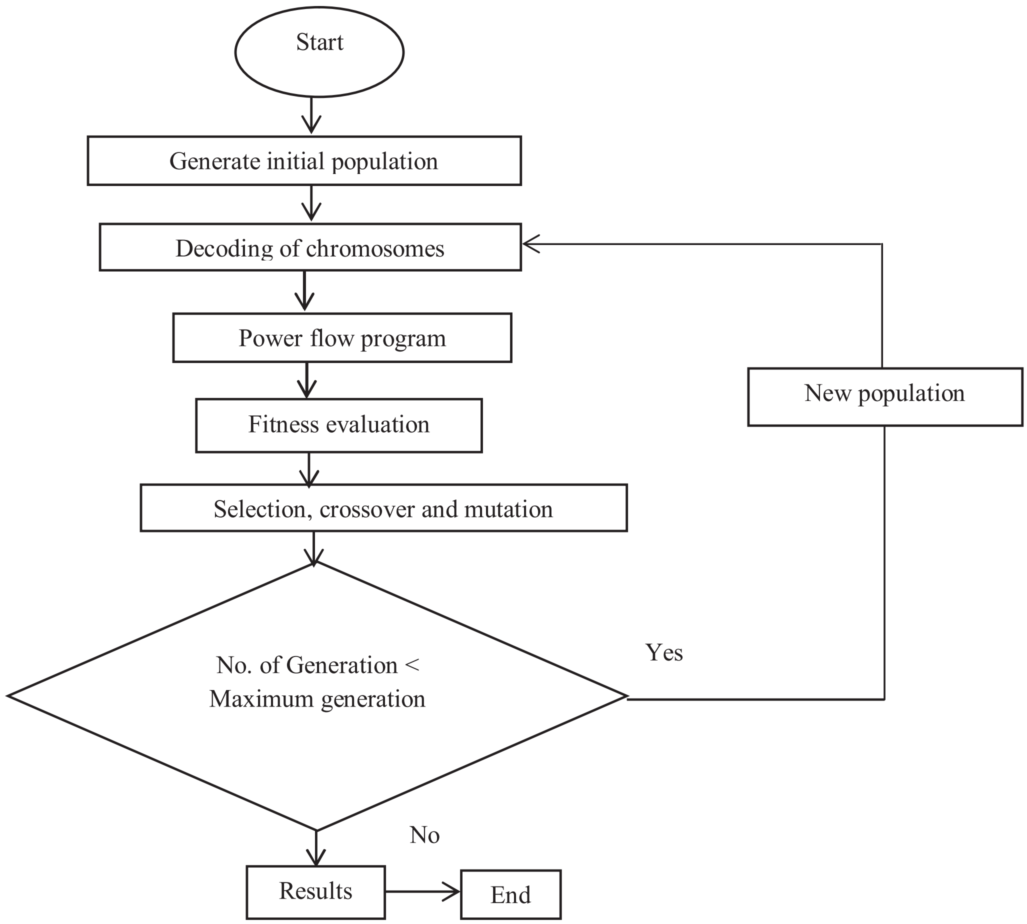

Figure 2.5 Flow chart for optimal location of SVC device using GA

2.4.2.4 Optimal Location of FACTS Device Using GA

Radu and Besanger (2005) showed that cascading outages leading to blackout can be prevented by optimal insertion of FACTS devices in power systems. A Genetic Algorithms approach was used to solve the combinatorial problem of FACTS devices optimal location. The FACTS devices were optimally placed in order to maximize the power system security. Optimizations were performed on three parameters: the locations of the devices, their types, and their rates.

Genetic Algorithm can be used to solve multi-objective optimization problem (Sumathi and Surekha 2010). Pisica et al (2009) presented optimal SVC placement in electric power systems using a genetic algorithms based method. An application of genetic algorithms was presented for finding the best location of SVC within a power network, with the objective of reducing power losses and voltage deviations and costs. Alabduljabbar and Milanovic (2006), Bakirtzis et al (2002), Malikand Srinivasan (2010) investigated OPF and the Genetic Algorithm (GA) based optimization procedure to solve the problem of optimal allocation of FACTS device.

Arabkhaburi et al (2006) looked into optimal placement of UPFC in power systems using genetic algorithm. GA was used to determine optimal location of UPFC in the power system. Optimal location was meant to find line number for UPFC location and its parameters for specified number of UPFCs. The system loadability was applied as measure of power system performance.

Nikoukar and Jazaeri (2007) suggested application of genetic algorithm for optimal location of FACTS devices in a power system. GA was applied to determine the location of TCSC and SVC devices in a power system. Their type and rated value were simultaneously optimized. Baghaee et al (2008) presented optimal multi-type FACTS Allocation using genetic algorithm to improve power system security. The security index for contingency analysis of power system, cost function of FACTS devices and power system losses were optimized.

Gerbex et al (2001) applied GA to seek the optimal location of multi-type FACTS devices in a power system. The optimizations are performed on three parameters: the location of the devices, their types and their values. The system loadability is applied as measure of power system performance. Four different kinds of FACTS controllers are used and modeled for steady-state studies: TCSC, Thyristor Controlled Phase Shifting Transformer (TCPST), Thyristor-Controlled Voltage Regulator (TCVR) and SVC. Simulations were done on IEEE Power Flow Test Cases (Power System Test Case Achieves).

Metwally et al (2008) presented optimal allocation of FACTS devices in power system using genetic algorithms. GA was used to find optimal locations of SVC. The objective cost function, which consists of the investment costs for this type of FACTS devices and the generation costs were minimized. Narmatha Banu and Devaraj (2008) achieved optimal power flow for steady state security enhancement using genetic algorithm with FACTS devices, avoiding line overload and single line outages. The optimizations were performed on two parameters: the location of the devices, and their values. The approach used an index called the single contingency sensitivity index to rank the system branches according to their suitability for installing TCSC and TCPST.

Shaheen et al (2008) checked optimal location and parameters setting of UPFC based on GA and PSO for enhancing power system security under single contingencies. Contingency analysis and ranking process have been performed to determine the severest line tripping contingencies considering line overloads and bus voltage violations as a performance index. GA and PSO have been successfully applied to find out the optimal location and parameters setting of UPFC corresponding to the determined contingencies scenarios.

Malakar et al (2010) and Belazzoug and Boudour (2010) used non-dominated sorting genetic algorithm (NSGA-II) and multi-objective optimal power flow to achieve optimal location and size of FACTS Devices—TCSC and SVC and reduction in generation cost and real power loss.

In research done by Marouani et al (2009), NSGAII has been applied to multiobjective VAR dispatch optimization problem with UPFC device in order to compute real power loss and deviation in voltage. Marouani et al (2011) used GA with a sensitivity based approach to find suitable placement of FACTS devices—TCSC and UPFC—along the system branches based on the Contingency Severity Index (CSI) values and to avoid system overloads and to improve system security margin in single and double contingencies. The type of device to be placed, cost of installation and their settings were taken as the optimization parameters for both single and double contingencies.

Prashant Kumar Tiwari and Yog Raj Sood (2011), Cai et al (2004) used a genetic algorithm based approach for optimal location of FACTS devices—SVC, TCSC, TCPST, and UPFC—in power system using genetic algorithm to determine the suitable type of FACTS controllers, its optimal location and rating of the devices in power systems and also to simultaneously determine the active power generation for different loading conditions.

Huang and Negnevitsky (2008) examined a messy genetic algorithm based optimization scheme for voltage stability enhancement of power systems under critical operation conditions. The placement of SVCs in a power system has been posed as a multi-objective optimization in terms of maximum worst-case reactive margin, highest load voltages at the critical operating points, minimum real power losses and lowest device costs.

Genetic-algorithm (GA) based method to determine the optimal siting (best placement) of FACTS controller with the consideration of economics and cost effectiveness is proposed by Leung and Chung (1999). Vijayakumar et al (2007) examined an alternate algorithm to solve OPF problem incorporating FACTS Devices— TCSC and UPFC—in a multi machine power system with the help of GA using which they optimized the location of FACTS devices, their type and rated values

Najafi et al (2006) suggested a simultaneous GA and CPF to determine optimal location of SVC, to improve voltage profile and to maximize system loadability with and without generators Mvar limits. Narayana Prasad Padhy et al (2004) proposed a GA based optimal reactive power planning model incorporating FACTS. Genetic algorithm was performed on two parameters: the optimal location of the devices and their control parameter.

Karami et al (2009) emphasized the importance of FACTS elements allocation to describe the effect of FACTS devices— SVC and TCSC—and placement of these devices in the electric power system. Optimal allocation and control of these devices will be very important for International Organization for Standardization (ISO) or other power market regulators. The best location, appropriate size and setting of FACTS devices are important in the deregulated electricity markets.

Lu et al (2007) proposed a reactive power planning model, which incorporates FACTS device. The optimal location of TCSC, TCPST, TCVR and SVC and their control parameters were optimized by a novel Bacterial Swarming Algorithm (BSA) to minimize the real power losses and also to improve voltage profile. Results were compared with GA and PSO.

2.4.3 Hybrid PSOGA

Hybrid PSOGA algorithm combines the standard velocity and position update rules of PSO with the ideas of selection and crossover from GA. The algorithm is designed so that the PSO performs a global search and the GA performs a local search, (Amir Mohammadi and Mostafa Jazaeri 2007).

2.4.3.1 Proposed Algorithm for Hybrid PSOGA

The proposed algorithm for the optimal placement of SVC device using hybrid PSOGA is given below:

Step 1 : Initialize velocity, P_{best}, G_{best}, number of particles and maximum iteration.

Step 2 : For each particle, initialize SVC size and location of SVC.

Step 3 : Check whether maximum iteration is reached, if yes, then obtain the optimum location and rating of SVC and go to step 9; if no, continue.

Step 4 : Run power flow program and compute objective function.

Step 5 : For each particle, determine and store P_{best}.

Step 6 : For each particle, determine and store G_{best}.

Step 7 : Update velocity and position using equations (21)-(23).

Step 8 : If feasibility solution is obtained then go to step 3. Otherwise relocate particle to feasible position of search space.

Step 9 : Get the last population obtained from PSO as initial population for GA.

Step 10 : Run power flow program.

Step 11 : Evaluate fitness value of all the individuals.

Step 12 : Select a new population from the old population, based on the fitness of the individuals as given by the evaluation function

Step 13 : Apply genetic operators (mutation and crossover) to members of the population to create new solutions.

Step 14 : Evaluate the fitness value of new chromosomes and insert them into the population.

Step 15 : If the maximum iteration is reached, stop and return the best individual if not, go to step 12.

2.4.3.2 Proposed Flowchart for HYBRID PSOGA

The proposed flowchart for optimal location and rating of SVC device using hybrid PSOGA is shown in Figure 2.6.

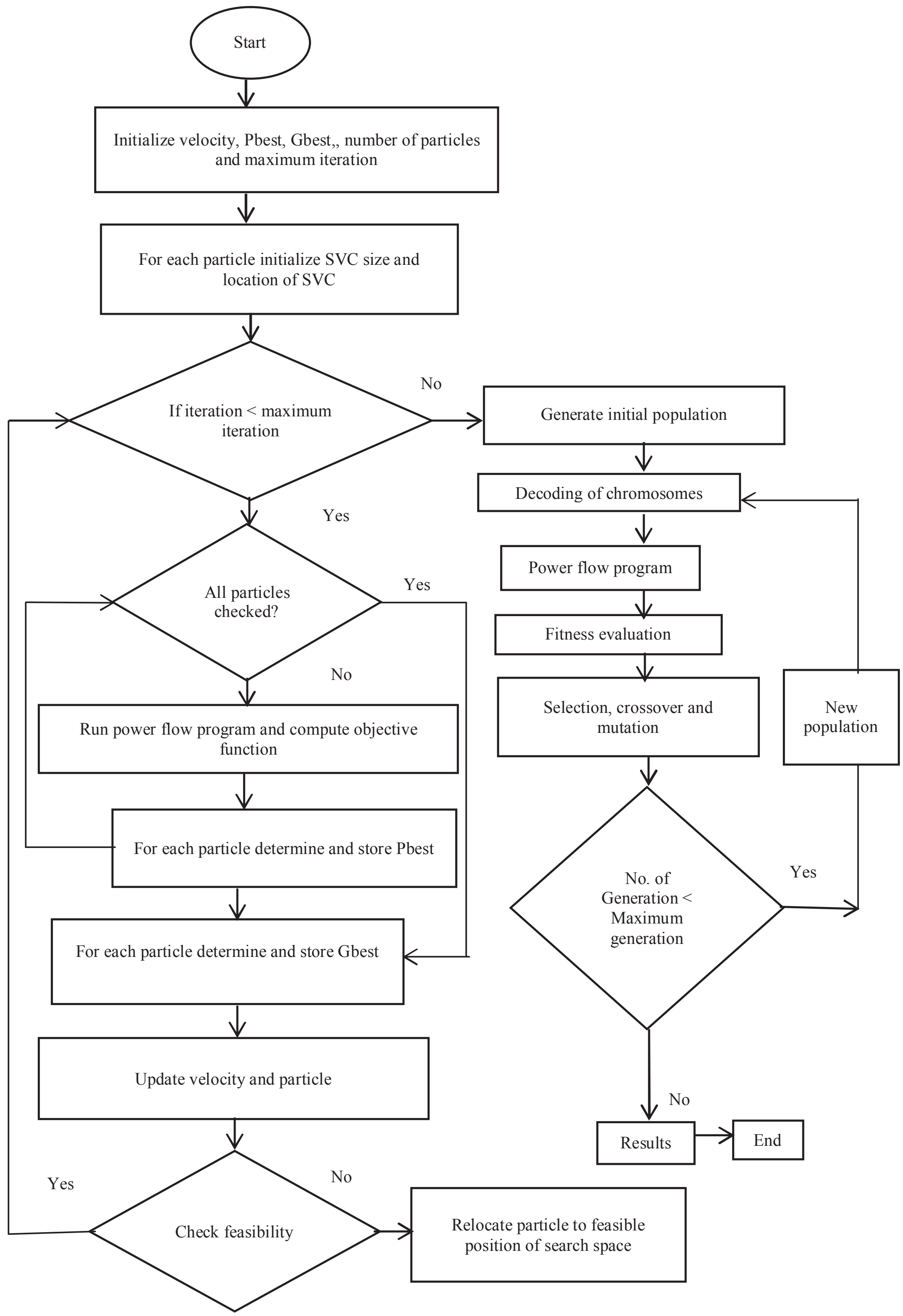

Figure 2.6 Flow chart for optimal location of SVC device using hybrid PSOGA

2.4.3.3 Optimal Location of FACTS Device Using Hybrid PSOGA

Amir Mohammadi and Mostafa Jazaeri (2007), Iraj Kheirizad et al (2008) proposed a hybrid particle swarm optimization-genetic algorithm—a combination of PSO and GA—for optimal location of SVC devices in power system planning, minimizing total power loss and the cost of installation and for keeping the voltages at different buses within acceptable levels. Drawbacks of PSO and GA have been overcome by the new algorithm.

Whei-Min Lin et al (2009) applied ACO plus GA for optimal capacity and location of a new STATCOM with ECI model in a power system. The proposed method demonstrates the improvement of voltage stability margin. Parizad et al (2009) proposed harmony search algorithm and GA to determine optimal location of FACTS devices— Thyristor Controlled Phase Angle Transformer (TCPAT), UPFC, and SVC—in a power system to improve power system stability.

A strategy for placement and sizing of shunt FACTS controller using Fuzzy logic and Real Coded Genetic Algorithm is spurred by Phadke et al (2009). A fuzzy performance index based on distance to saddle-node bifurcation, voltage profile and capacity of shunt FACTS controller is proposed in this research work.

Sundareswaran et al (2009) proposed voltage profile enhancement through optimal placement of FACTS devices, using Queen-Bee assisted GA. The proposed algorithm is a suitable modification of a standard GA incorporating the evolution of a queen bee in a hive. Hybrid tabu search and simulated annealing approach is proposed by Bhasaputra and Ongsakul

(2002) to minimize the generator fuel cost in OPF control with multi-type (FACTS) devices—TCSC, Thyristor Controlled Phase Shifter, UPFC and SVC.

2.5 SUMMARY

From the literature survey, it has been observed that voltage stability and voltage collapse are very important problems to be considered. Voltage stability index can be determined by various methods. Different techniques used for voltage stability analysis are P-V Analysis, Q-V Analysis, Modal Analysis and Time-Domain Analysis. Critical bus, critical transmission line and critical generator can be found by any one of voltage stability analysis technique. Using continuation power flow method maximum loadability margin can be found. FACTS devices can increase voltage stability margin, reduce transmission line loss and reactive power and voltage at all the load buses can be controlled within the limit. GA and PSO biologically inspired optimization techniques are used to obtain optimum location and optimal rating of FACTS devices to maximize the voltage stability margin, reduce the real power losses, minimize load voltage deviation, reduce cost of generation and cost of FACTS devices to improve voltage stability of the given power system. Summary of other researcher results is given in Table 2.1.

Table 2.1 Summary of other researcher results

OTHER RESEARCHER	SUMMARY
Saravanan et al (2005)	The solutions for optimal location of FACTS devices to minimize the cost of installation of FACTS devices and to maximize system loadability for IEEE 6 and 30 bus systems were obtained using PSO. For IEEE Six bus system, using SVC the maximum system loadability obtained is 110% and the minimum installation cost for SVC is \$ 9.73×10^6. For IEEE 30 bus system, using SVC the maximum system loadability obtained is 128% and the minimum installation cost for SVC is \$ 0.52×10^6.
Najafi et al (2006)	Simultaneous GA and CPF are used to determine optimal location of SVC for the IEEE 57-bus test system. After optimal allocation of SVC maximum system loadability increased from basecase λ =1 to λ=1.63 with generators MVAR limits and it increased to λ= 1.78 without generator MVAR limits, λ is loading parameter. Optimal SVC placements are bus numbers 15, 31, 36, 42, 52 and 56 and MVAR ratings are 50, 7.8, 11.28, 15.3, 5.49 and 3.76 respectively.
Lu et al (2007)	Optimal allocation of FACTS Devices have been found for IEEE 30-bus and IEEE 118-bus test systems using BSA, PSO and GA. Power losses obtained by BSA, PSO and GA for the IEEE 30-bus system are 6.4989 MW, 8.2172 MW and 12.0739 MW respectively. Optimal location of SVC is bus 22 and rating is -30.1722 MVAR. Real power loss has been decreased from 15.7634 MW to 6.4989 MW, which is a reduction of about 60%. Power Losses obtained by BSA, PSO and GA for the IEEE 118-bus system are 297.6209 MW, 320.1823 MW and 359.6403 MW respectively. Real power loss has been decreased from 374.3548 MW to 297.6209 MW. Optimal location of SVC is bus 38 and rating is 70.1628 MVAR.
Nikoukar and Jazaeri (2007)	GA is applied to determine the location of SVC devices in the modified (without shunt capacitors) IEEE 30 bus test system. Real power loss is 17.895 MW and reactive power loss is 24.862 MVAR when SVC is not used. Real power loss is 17.695 MW and reactive power loss is 22.3 MVAR when SVC installed at bus 24 with 25 MVAR

Table 2.1 (Continued)

OTHER RESEARCHER	SUMMARY
Metwally et al (2008)	Optimal Allocation of FACTS Device has been found for the IEEE 14-bus test system using GA. After the optimization, SVC at bus 5 is the best location. The rate of the SVC placed at this bus is 51.66 MVAR. Fuel cost is 1064 $/hr.
Sundareswaran et al (2009)	Optimal placement of FACTS devices using Queen-Bee assisted GA have been found for IEEE 30 bus system. Voltage stability index is 0.8393 p.u. when SVC is not used. Voltage stability index is 0.8203 p.u. when SVC's are located randomly at buses 7, 12 and 30. Voltage stability index is 0.4406 p.u. when SVC's are located optimally at buses 7, 12 and 30.
Parizad et al (2009)	Placement of multi-type FACTS devices based on Harmony Search and Genetic Algorithm has been found for IEEE 30 bus system. Optimal location and related parameters for SVC using GA are: location of SVC is 30. Size of SVC is 21.23 MVA, Real power loss is 5.28 MW and L (stability index) is 0.1431. Optimal location and related parameters for SVC using HSA are: location of SVC is 12. Size of SVC is 12 MVA, Real power loss is 5.22 MW and L (stability index) is 0.14.
Pisica et al (2009)	Best location of SVC using GA has been found for test network 220 kV, 13 nodes test system. Bus number 10 is the most suitable location for the SVC, and 63% of the results suggest that reactive power of SVC installed is 143 MVAR.
Sundareswaran et al (2010)	Optimal locations for 3 SVC's in an IEEE 30 bus system using PSO have been found. Voltage Stability Index is 0.8893 p.u. when SVC is not used. Voltage Stability Index is 0.7781 p.u. when SVC's are located randomly at buses 8, 13, 23. Voltage Stability Index is 0.4558 p.u. when location of SVC's at buses 11, 21 and 24 is identified using PSO with 10 particles. Voltage Stability Index is 0.4406 p.u. when location of SVC's at buses 11, 21 and 30 is found using PSO with 50 particles.

Table 2.1 (Continued)

OTHER RESEARCHER	SUMMARY
Malakar et al (2010)	Minimum cost of generation occurs when SVC is placed at its best location (bus 24) with 4.2 MVAR lagging reactive power whereas; gives least power loss when it is placed at bus 8 with leading reactive power of 50 MVAR. Fuel cost is 575.94 $/hr and Power loss is 1.934 MW when SVC is used. Fuel cost is 576.60$/hr and power loss is 2.01MW when SVC is not used.
Prashant Kumar Tiwari and Yog Raj Sood (2011)	Optimal allocation of FACTS devices have been found for the IEEE 30-bus test system using GA. When no FACTS controllers are used, total cost is 781.24 $/Hour, total demand $P_d$is 283.4 MW, total generation Pg is 287 MW and total loss P_L is 2.95 MW. When the loading at bus 2 is increased from 21.7 MW to 51.7 MW, the SVC is selected at line 36. The rating of SVC is 73.38 MVAR, total cost is 881.87 $/Hour, total demand P_d is 313.4 MW, total generation Pg is 315.93 MW and total loss P_L is 2.53 MW.