Chapter 2
FACTS DEVICES AND COMPUTATIONAL TECHNIQUE

2.1 FACTS Devices

This section describes the many FACTS devices that use heuristic search techniques to optimize location and size. Researchers have used Nemours' methods in the past to address the issue of ideal FACTS device placement. A series-coupled controller, shunt-connected controller, combination series and shunt controller, or collective shunt and series controller, is how this device might be classified. Shunt controllers manage the power flow in the lines, while series controllers control the voltage at the bus. There are many FACTS devices used in power systems, but some important FACTS strategies, like TCSC, SSSC, SVC, STATCOM, TCPST, UPFC, and Interphase Power Flow Controller, are used often (IPFC).

General device placement is divided into three types: heuristic search, linear encoding, and analytical method. The problem of optimal location and size is one for which combinational analysis and heuristic search methods are the best tools for resolving the real problems of the power system.

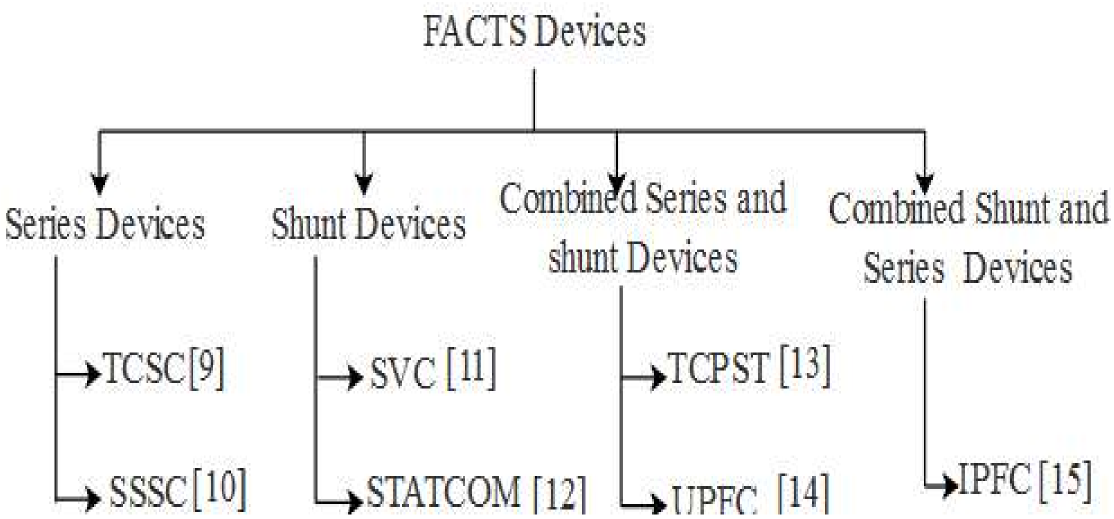

Figure 2.1 Taxonamy of FACTS deviices

To identify the ideal solution for FACTS devices, intelligent optimization methods like GA and PSO are applied. These algorithms optimise fitness functions with several objectives. It is difficult to choose the appropriate penalty factors or weights to be utilised in the fitness function in order to reflect the relative importance of different purposes, even when the minimal degree of fulfillment among the objectives is not guaranteed in these algorithms. Most conventional techniques have focused on power loss and voltage variation. Voltage stability improvement has received relatively little direct effort. The taxonomy of FACTS devices is displayed in Figure 1. Following is a brief discussion of the steady-state schemes of the selected FACTS devices and their models.

A. Static Synchronous Series Compensators (SSSC) device

The SSSC controller is one of the significant FACTS devices aimed at power transmission series compensation; it can be considered a synchronous voltage resource. In sequence with TL, the SSSC device can insert sinusoidal voltage with variable, controllable amplitude and phase angle.

The injected voltage is almost in quadrature with line current (LC). A small region of injected voltage that is in phase with LC provides the losses in the inverter. The maximum of the injected voltage, which is in quadrature with the LC, provides the effect of inserting capacitive reactance in series with the TL. This variable reactance influences the electric power flow in the TL. The stable state power flow model of SSSC depends on the possibility of altering voltage size and phase angle. This value is changed routinely to limit the power division at a specified value [17].

B. Static VAR Compensator

The SVR device is a shunt-connected device that is installed in parallel with a bus, and it has the capability to produce power at the point of association. The SVC is a joint term for a Thyristor Controlled Reactor (TCR) and a Thyristor Switched Capacitor (TSC). It performs in two diverse modes: inductive mode and capacitive mode. reactive power absorbs in inductive mode and reactive power injects in capacitive mode, which is shown as an ideal reactive power injection at the bus. The reactive power is restricted as follows: -100 MVAR [18].

C. Static Synchronous Compensator (STATCOM)

The voltage profile can be made better by using the STATCOM. The TL receives current from the shunt controller, which is what it is. The system voltage of the STATCOM device is greater than the generator voltage. This measures the reactive power, which may be used on both current and voltage source converters and is less than generated reactive power. A load bus is where the FACTS device is always situated. The bus is converted from a PV bus to a PQ bus where the STATCOM device is being installed. As a result, the STATCOM device is regarded as a synchronous generator whose voltage is set to 1 and whose real power output is 0 [19]. Thyristor-Controlled Phase Shifting Transformer (TCPST) TCPST is a most applicable model of FACTS device that adjusts the angular variance between the lines. Presently, politics, financial, social, and ambient factors have delayed the construction of a few transmission lines. Next, studies that create the possibility of installation of equipment to flexible and enhance the capacity of the transmission networks. But, the better choice for installation of this equipment is not a simple task because of the difficulty of an electric system [20].

2.2 Literature Review

Quasi-Oppositional Chemical Reaction Optimization (QOCRO) was introduced by Dutta et al. [16] to determine the ideal distribution and size of the FACTS devices. To stabilize the voltage magnitude, the QOCRO integrates quasi-oppositional based learning (QOBL) with chemical reaction optimization (CRO). This QOCRO-based allocation considers the SVC and TCSC devices, which are two FACTS devices. The IEEE 14 bus and the IEEE 30 bus are two distinct bus systems in which this QOCRO technique has been validated. The voltage stability and convergence speed are enhanced by incorporating the QOBL and CRO. Only three goal functions—minimization of voltage variation, real power loss, and voltage stability index—are considered by this system.

To avoid the reactive power dispatch (RPD) issue, Reddy et al. [17] created a hybrid optimization combining KGMO and Particle Swarm Optimization (PSO) for the best distribution of FACTS. Three separate facts—SVC, TCSC, and UPFC—are utilized in this work. The 30-bus test system is used to validate the hybrid KGMO-PSO algorithm. By placing FACTS devices at the right nodes, power loss and voltage deviation are minimized. The PSO utilized in this KGMO-PSO readily enters local optimum conditions when applied to a high dimensional space.

The Multi-Population-Based Modified Jaya (MPMJ) algorithm was introduced by Maru and Padma [18] for the best location of STATCOM. This algorithm considers three distinct objective functions: decreasing power loss, increasing voltage deviation, and increasing the static voltage stability margin. Here, the MPMJ in IEEE 30-bus systems is validated using two separate bus systems. Utilizing this MPMJ with three objective functions advances the real power loss and static voltage stability margin. However, the generation cost of FACTS devices is not considered by MPMJ-based optimal allocation in its objective functions.

To optimally distribute the SVC in the transmission scheme, Sen et al. [19] developed the hybrid algorithm by fusing the CRO and Cuckoo Search Algorithm (CSA). When putting the SVC, a number of factors are taken into account, including the nsmi time period, line loss reduction, voltage stability, power generation minimization, and annual cost of power generation. The placement of FACTS devices in three bus systems—IEEE 14-bus, 30-bus, and 57-bus transmission systems—under strongly loaded conditions is examined using a hybrid CSA-CRO-based approach. The hybrid CSA-CRO technique's optimal SVC allocation does not take into account the total voltage deviation. To prevent losses in the bus system, the voltage deviation should be considered for an efficient transmission system.

The Whale Optimization Algorithm (WOA) has been demonstrated by Nadeem et al. [20] for the ideal sizing and allocation of FACTS, specifically the SVCs, TCSCs, and UPFCs. Here, lowering the functional cost of the network—which considers hardware expenses and active power losses—was the key objective. The proposed WOA was then used to identify some ideal evaluations for the given devices as well as for the best management of SVC, TCSC, and UPFC using the reactive power sources that had previously been present in the system (transformers and generators). However, once the reactive power loading is changed, the results may be inaccurate.

2.3 Meta heuristic optimization Technique

Advanced methods for figuring out an optimization problem's optimality are called optimization algorithms. An algorithm is a method used to generate outputs for a set of inputs under certain restrictions in mathematics (Blum and Roli, 2003) m is a method that generates outputs for a collection of inputs while adhering to certain restrictions (Blum and Roli, 2003). Every optimization technique has an objective function that is used to assess goals in the context of restrictions. To maximize or minimize the objective function, optimization algorithms first define the search space (Yang, 2010). The programme uses the right mathematical methods to explore the space for optimal solutions after formulating an optimization issue. Finding the ideal solution, which depends on the goals, is one option., which takes time, or to find a near-optimal solution with less time difficulty.

There is no efficient method that can be employed in every situation when choosing an algorithm for distributed systems since there are too many variables to consider. Instead, the optimization method has clear goals and objectives. There are various categories into which optimization approaches can be divided. A typical classification separates algorithms into deterministic and stochastic algorithms based on the nature of the algorithm and the mechanism for finding answers (Yang 2010). While stochastic algorithms are predicated on the randomness of the path and variables, deterministic algorithms follow a repeating path and set of variables. For instance, because genetic algorithms are based on unpredictability, when they search for an optimal solution, the population of options varies every time. While the pathways in each population are repeated, the outcomes of stochastic algorithms, on the other hand, do not significantly alter. Some methods mix deterministic and stochastic algorithms to take use of each approach's strengths while mitigating its weaknesses.

Heuristics and meta-heuristics are the two categories into which stochastic algorithms themselves can be subdivided. Heuristic approaches find an excellent optimal solution with little computational expense, but they cannot be relied upon to do so (Madni et al., 2016). Meta-heuristic algorithms, which combine randomization and local search, typically outperform simple heuristics (Yang, 2010). The distinction between heuristic and meta-heuristic algorithms is not given a clear explanation. But some academics refer to all stochastic algorithms that have a global search and a randomness attribute as meta-heuristics (Gendreau and Potvin, 2005).

When used for global optimization, randomization in metaheuristic algorithms offers a way to transition from the local space to the global space (Blum and Roli, 2003). On the basis of one or more objectives, meta-heuristic algorithms are used to obtain close to optimal solutions in a reasonable amount of time (Gendreau and Potvin, 2005). When compared to deterministic algorithms, meta-heuristic algorithms deliver higher-quality and faster outcomes (Tsai and Rodrigue 2014).

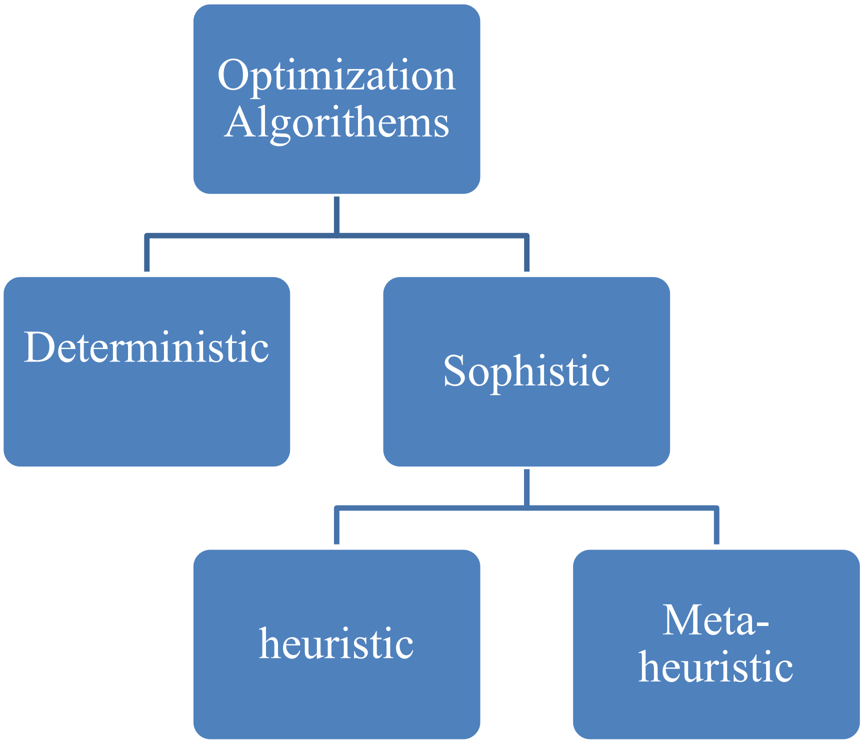

Figure 2.2 Classification of Optimization Techniques

2.3.1 Swarm Intelligence Algorithms

Swarm intelligence algorithms, which are based on the social behavioral models of pests or other animals, provide several related methods for resolving issues that resemble biological swarms (Blum and Li, 2008). The SI algorithms use several swarms to search for a solution by exchanging information in a search space. In particular, the SI is a meta-heuristic that was created by modeling the behavior of actual insect swarms or swarms to address difficulties (Kennedy, 2011). SI algorithms are used to optimize distributed-structured complex issues. They can also be utilized in systems with elastic and flexible characteristics without changing the overall structure. So many SI techniques, such ACO and PSO (Guo et al.), have been used in cloud computing to enhance resource scheduling. ACO and PSO (Guo et al. (2012)). Details on each of these algorithms will now be presented.

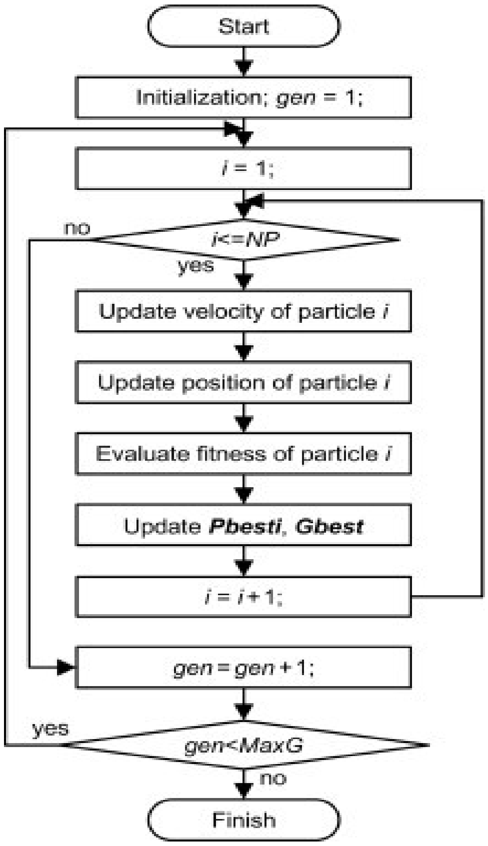

Figure 2.3 Swarm Intelligence Algorithm

2.3.2 Particle Swarm Optimization Algorithm

PSO is a global search technique that uses a collection of particles with random positions and velocities. The velocity of each particle in PSO, which reflects its movement in the search space, is dynamically adjusted depending on the behavior of the particle in question. Particles seek the explanation space by changing their position and velocity because they tend to travel towards better points inside the search space (Trelea 2003). There are several SI algorithms in use, but PSO has been demonstrated to perform better and be more sophisticated in large-scale situations. Associated to other SI algorithms, such as genetic algorithms, it takes less time to compute. Additionally, it employs actual numerical values rather than binary encoding GA does. Thus, in the current research, a PSO algorithm will be used in optimization.

In terms of computational time, the PSO method offers effective performance in a distributed setting like cloud computing, where it is quicker than meta-heuristic algorithms like GA and ACO. In terms of processing and implementation, PSO was discovered to be quicker and easier than GA, and it offers a few parameters to tweak and advance the convergence speed, according to Pongchairerks (2009). The task scheduling problem will be optimized in this study using PSO.

For example, PSO is constrained by local optima and a slow convergence rate in large spaces. PSO has two options for resolving these issues. The PSO algorithm can first be modified by altering certain of its formulas and parameters. Additionally, it iss used in conjunction with other meta-heuristic techniques. According to the goals and the nature of the problem, the two methodologies will be applied in this thesis. For task scheduling and negotiation, the modified PSO will be utilized; for VM allocation, the conventional PSO will be used. It will be paired with another algorithm to enhance PSO's performance in data clustering with the K-means technique.

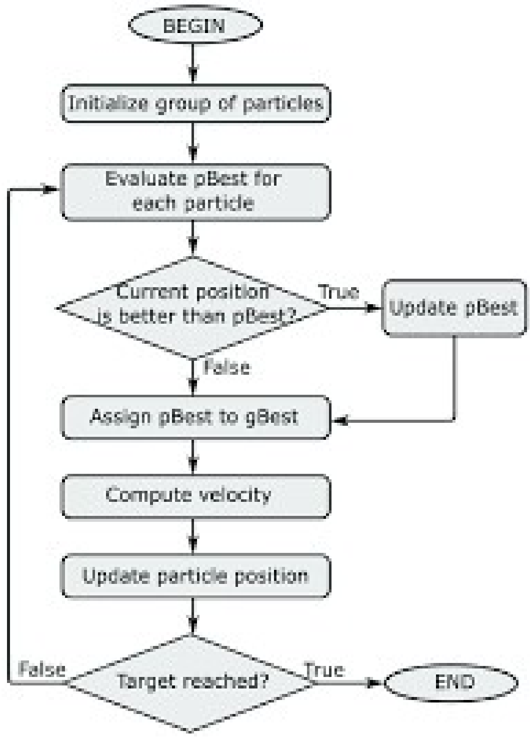

Figure 2.4 PSO Algorithm

2.3.3 Ant Colony Optimization Algorithm

ACO is a meta-heuristic algorithm which emulates the behavior of ants as they search for food to solve complex optimization problems. It makes use of a technique to mimic the cooperative pheromone-based behavior of real ant colonies. In their search for food, ants follow a path and spread pheromones along the way. By smelling the pheromone, additional ants can then follow the trails to the food source (Shishira et al., 2016). Because more pheromones have been collected on the shortest path, most ants choose it (Dorigo et al., 2006; Tawfeek et al., 2015).

The versatility, resilience, and redundancy of the ACO algorithm are only a few of its many benefits. Discrete optimization issues are resolved with ACO techniques by determining the shortest route to the desired outcome. Additionally, it has been effectively applied to a variety of other problems, including routing issues in dynamic networks, multidimensional knapsack problems, travelling salesman issues, job shop scheduling, and task scheduling in cloud environments (Shishira et al. 2016).

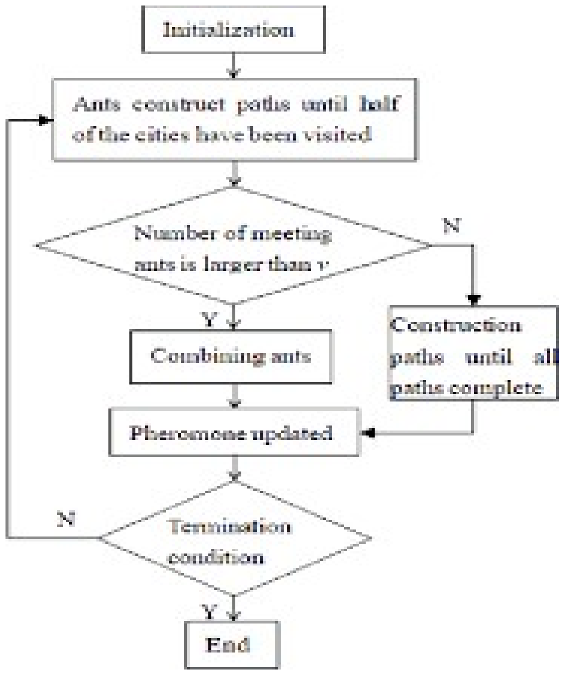

Figure 2.5 ACO Algorithm

2.3.4 Evolutionary Algorithms

In order to address optimization issues, evolutionary algorithms use ideas since biological evolution, such as reproduction, mutation, and recombination (Simon 2013). The implementation of EA algorithms varies based on the problems that need to be solved yet they all have the same fundamental concept. Due to the complexity of the ideal solution, evolutionary algorithms are a set of meta-heuristics that are utilised to tackle a variety of complex issues (Simon, 2013). The Genetic Algorithm is the most widely used EA algorithm.

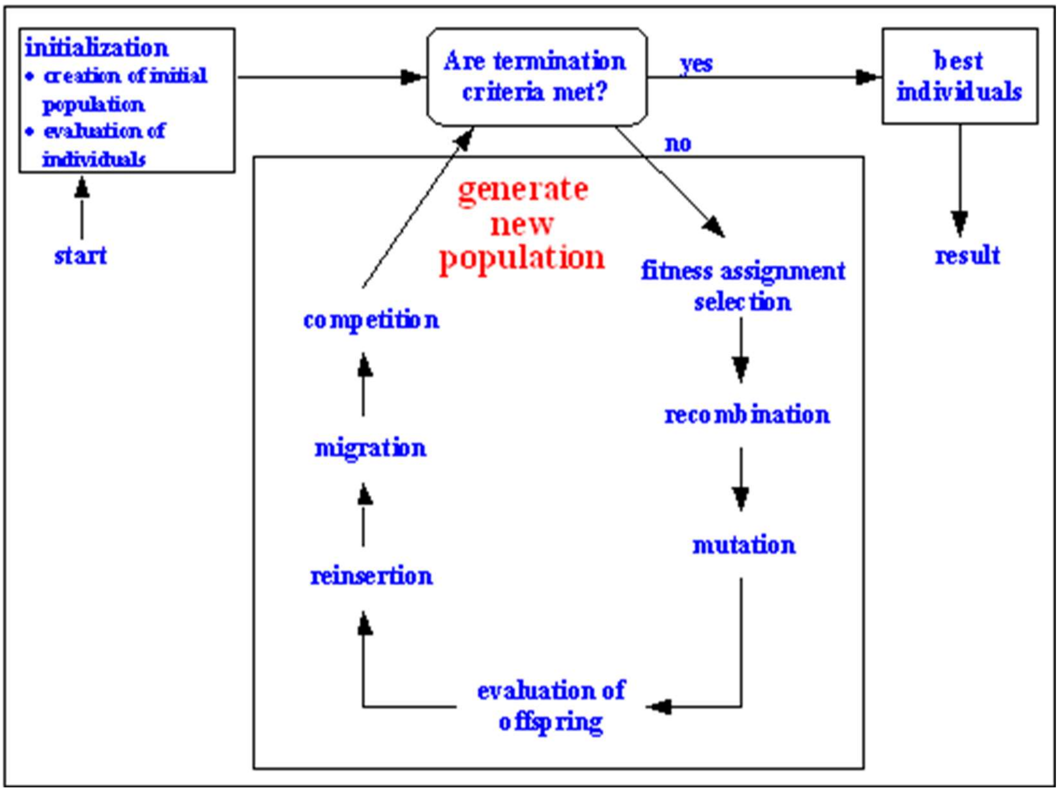

Figure 2.6 Evolutionary Algorithms

2.3.5 Genetic Algorithms

One of the evolutionary algorithms, the GA technique, seeks to solve large-space problems with a close-to-optimal result (Whitley 2014). To simulate the process of natural evolution, which involves the encoding of chromosomes, selection of genetic manipulation and evolution, crossover and mutation operations, and, finally, the generation and evaluation of new generations, the development of a GA method is based on natural selection and Mendel's laws of inheritance (Gendreau and Potvin, 2005). Due to the enormous number of parameters that need to be processed and encoded, 34 GAs require a lot of time during optimization.

The GA algorithm finds a nearly optimum solution and avoids becoming stuck in locally optimal solutions as compared to these algorithms' use in cloud computing environments. However, utilizing GA can take longer than PSO and there is no certainty that a global maximum will be discovered. ACO's disadvantage is that it is ineffective at balancing load because it begins randomly and occasionally misses the overall best option. ACO's convergence time is also ill-defined and dependent on the size of the problem space and the number of dimensions. In contrast, PSO uses a quick search and a straightforward calculation, but it is susceptible to premature convergence and local optima.

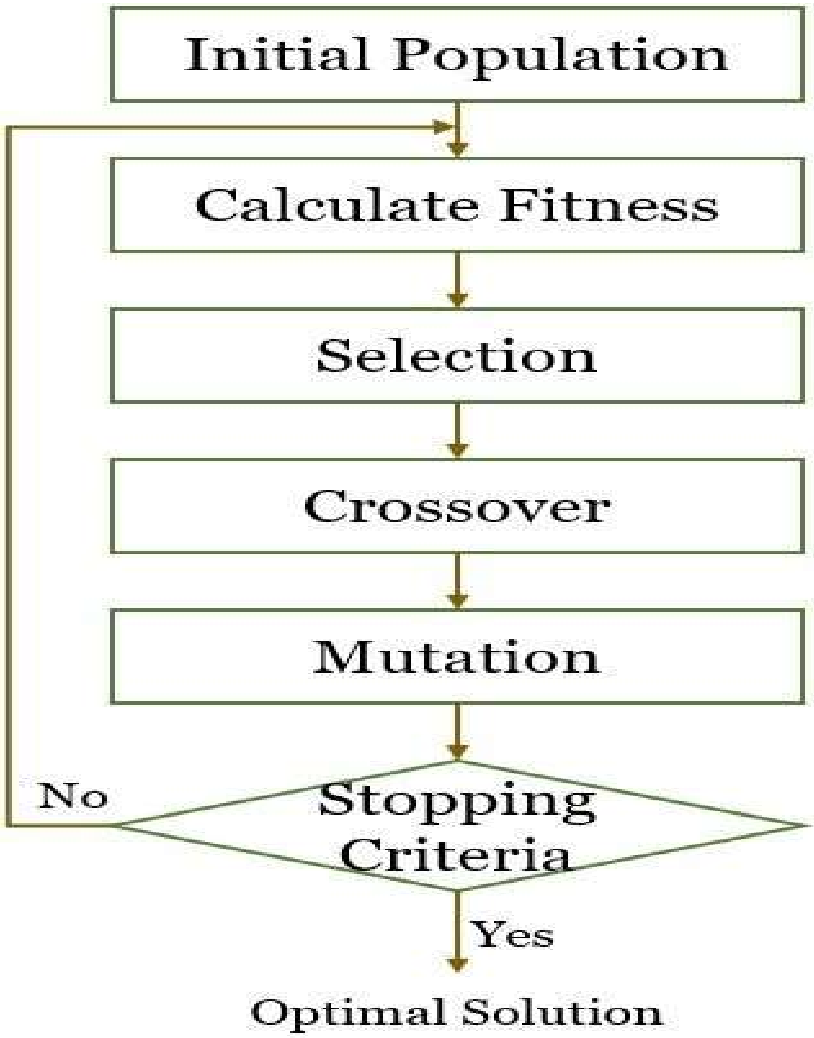

Figure 2.7 GA Algorithm

2.4 Objective and scope

- The generation cost, total voltage deviation (TVD), line loading (LL), and real power loss are the objective functions considered by the suggested methodology. Additionally, the IEEE bus system validates the best placement achieved with the hybrid technique.
- SVC, TCSC, and UPFC are three separate FACTS devices that are used to manage actual and reactive power in the transmission line system to increase voltage stability.
- The integration of the suggested strategy is utilised to position and size the FACTS devices in the best possible way. Additionally, the proposed method for placing FACTS devices is less computationally demanding. Additionally, it has higher chances of exploration and exploitation to get the finest benefits.
- By strategically positioning the FACTS devices, reactive power compensation and improved power transmission capability are made possible.

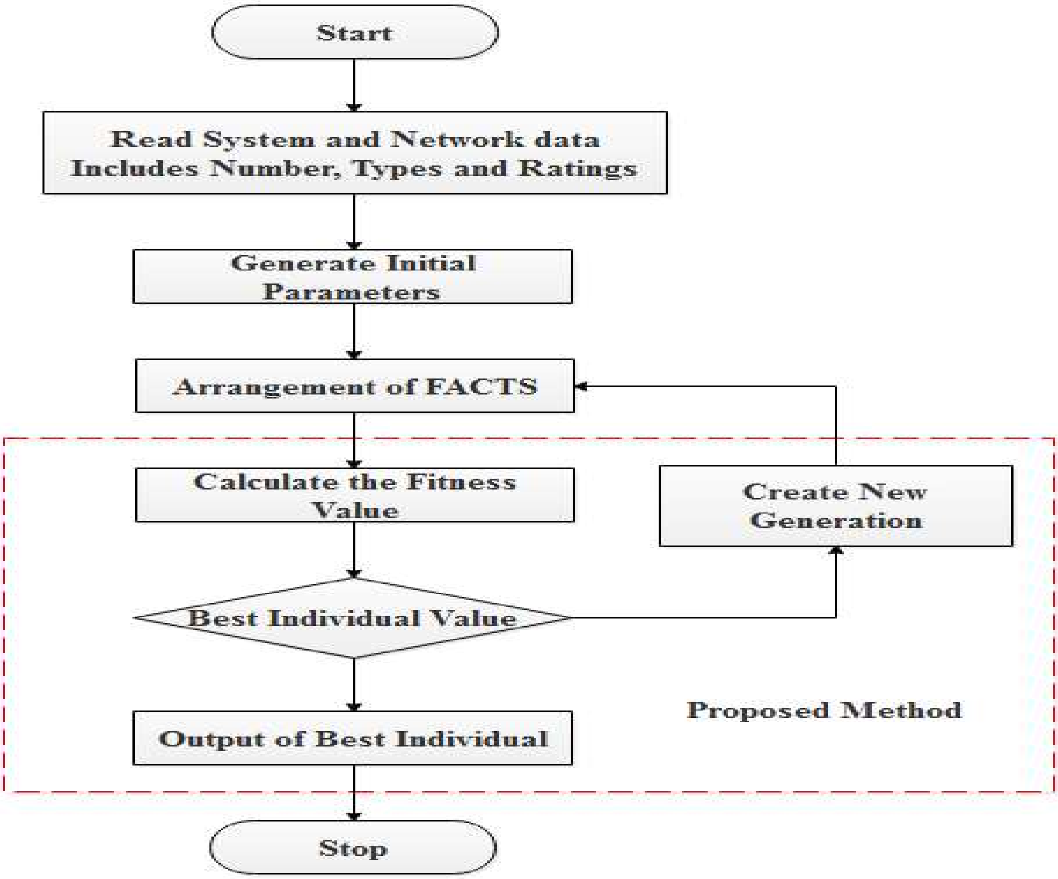

Figure 2.8 Proposed Algorithm