CAPACITOR SIZING AND PLACEMENT FOR OPTIMAL POWER SYSTEM OPERATION USING GENETIC ALGORITHM

Thesis submitted in partial fulfillment of the requirements for the award of degree of

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in
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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Capacitor Sizing and Placement for Optimal Power System Operation Using Genetic Algorithm"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Power Systems & Electric Drives* submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr. Sanjay K. Jain, Assistant Professor, EIED. The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ABSTRACT

The demand of the electrical energy is ever increasing and it is desired to use the existing transmission network to its thermal stability limits. The transmission capacity can be increased by the compensation at appropriate locations.

The reactive power compensation plays an important role in the planning of power system. This ensures a satisfactory voltage profile and a reduction in power and energy losses within the system. Reactive power also maximizes the real power transmission capability of transmission lines, while minimizing the cost of compensation.

In this thesis, the reactive compensation of power system is attempted using the shunt capacitors. The optimal location and sizing of shunt capacitors is attempted using GA, which is a search technique based on the principles of genetics and natural selection. The GA allows a population composed of many individuals to evolve under specified selection rules to state that maximizes the “fitness”. The loss minimization is considered on the objective function in the optimization problem.

The program is developed to decide the size and location on the basis of minimization of system loss. It is tested for IEEE-30 bus system. The results are also obtained by fixing the number of capacitors.

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CHAPTER-1

INTRODUCTION

1.1 OVERVIEW

During the past two decades, the increase in electrical energy demand has presented higher requirements from the power industry. More power plants, substations, and transmission lines need to be constructed. The long switching periods and discrete operation of circuit breaker make it difficult to handle the frequently changed loads and the system from dynamic variation and recover from faults and damp out the transient oscillations quickly. In order to compensate this, large operational margins and redundancies are maintained. This not only increases the cost, but also increases the complexity of the system.

Therefore, it is necessary to study the security and stability of the power system. The reactive power compensation are used to increase the stability and the security of the power systems.

The Reactive power compensation plays an important role in the planning of a power system. This ensures a satisfactory voltage profile and a reduction in power and energy losses within the system. Reactive power also maximizes the real power transmission capability of transmission lines, while minimizing the cost of compensation.

The increase of real power transmission in a particular system is restricted by a certain critical voltage level. This critical voltage is dependent on the reactive power support available in the system. Use of series and shunt compensation is one of the corrective measures to produce an acceptable voltage profile, minimize the loss of the investments and enhance the power transmission capability.

The general transmission system capacitor placement problem consists of determining the optimal location, size and type of capacitors, as well as considering the most economical method. In turn power and energy losses are minimized.

1.2 LITERATURE REVIEW

For capacitor sizing and placement in optimal power system operation, various researches have been taken into account. These researches provide various techniques and different algorithms for sizing and placement of capacitor bank in transmission line. Here, brief review of literature on capacitor placement is carried out.

In electrical installations, low power factor results in more losses in the power system and to compensate the losses, power factor correction capacitors need to be installed. Significant cost savings can be made through the application of power factor correction capacitors. Different researches have been done for power factor improvement methods. To improve power factor and reduce system losses, the most commonly used method is the placement of capacitor banks. But the capacitors installed should be of appropriate sizes and should be placed at appropriate location where they can reduce losses more effectively and significantly. Various methods and theories have been given by different researchers.

According to Shwehdi and Sultan **[18],** while deciding sizing and location of PFC (power factor correction), many designers tend to base their calculations on maximizing the revenue from such installation by minimizing insulation cost and maximizing the energy savings. But few emphases to the potential adverse affects caused due to interaction between capacitor and power system elements. Among the most common and potentially harmful phenomenon is the harmonic amplification that can result from the presence of a resonance in the power system close to the frequency of a nearby harmonic source **[5].**

Abdullah and Saibon **[2]** described Genetic algorithm for optimal reactive power dispatch. Authors presented an alternative approach to optimal reactive power dispatch by searching for transformer tap settings and the value of shunt capacitors to minimize the total system power loss. The algorithm is tested on IEEE 14 and 30 bus systems and their results are compared with those obtained using load flow calculation **[6].**

Hen. and Salama **[21]** used fuzzy approach for the placement and sizing of capacitor for optimal operaton. Hammad and Roesle **[36]** discussed the role of VAR compensators in Transmission systems. The authors highlighted the importance of VAR compensators in transmission systems in reducing the system losses and making the system more economically.

Miu and Chian **[35]** used GA based two-stage algorithm tailored for capacitor placement, replacement and control of general, large-scale, unbalanced distribution systems. The capacitor placement in three-phase distribution systems with nonlinear and unbalanced loads is discussed by Graninger **[34]**. The authors they presented forward backward sweep load flow to calculate feeder currents, network node voltage and network losses. GA is presented to solve combination method problem presented here. The important means of reducing the power loss of distribution system are combined to determine better optimization result.

Reactive Power Compensation Technologies by Abril & Quintero **[16]** presented an overview of the state of the art in reactive power compensation technologies helps to understand the basics of prescribed problem. The principles of operation, design characteristics and application examples of VAR compensators implemented with thyristors and self commutated converters were presented. Static VAR Generators were used to improve voltage regulation, stability, and power factor in ac transmission and distribution systems.

Landstrom **[34]** discussed the PFC with Thyristor-Controlled Capacitors in detail. The authors described that the FACTS devices can work effectively for compensation. Moran, et al **[35]** presented the Analysis and design of a Solid State VAR compensator. Paserba, **[37]** has researched on choosing GA parameters and also broaden the view of problems being solved. Recommendations of methods to improve GA performance have also been discussed.

Many approaches and methods have been proposed to solve optimization problems in **[38]**. The solution methods are broadly grouped under two major categories: deterministic and stochastic methods.

Deb **[44]** discussed deterministic methods; there are specific rules for moving from one solution to the other. Secondly algorithms are stochastic in nature, with probabilistic transition rules. The working principles of these algorithms are simpler and therefore, easier to understand. These algorithms have been able to obtain global optimal solutions in complex optimization problems.

1.3 OBJECTIVE OF WORK

The objective of this thesis is to design and implement a method for determining the optimal locations and sizes of shunt capacitor banks in a transmission system. The sizing and placement of shunt capacitors at few load buses for minimizing the losses both real and reactive has been identified to be attempted using GA, because of being a powerful optimization algorithm that mimics the natural selection and genetics and the ability to provide global optimum solution.

1.4 ORGANIZATION OF THESIS

The thesis is organized into five chapters.

The **chapter-1** summarized the overview of the problem, brief literature review, scope of work and organization of the thesis.

The **chapter-2** highlights the importance of reactive power compensation and the overview of the common types of compensation techniques used in modern power system.

The **chapter-3** explores the associated structure of a Genetic Algorithm and the problem using GA. The algorithm is also presented in this chapter.

The **chapter-4** outlines the results. The results of the system without compensation and with compensation after optimal sizing and location of capacitors are compared.

In **chapter-5**, the major conclusions are drawn and the scope for future work is discussed.

CHAPTER-2

COMPENSATION IN POWER SYSTEM

In a linear circuit, the reactive power is defined as the ac component of the instantaneous power, with a frequency equal to 100 / 120 Hz in a 50 or 60 Hz system. The reactive power generated by the ac power source is stored in a capacitor or a reactor during a quarter of a cycle, and in the next quarter cycle is sent back to the power source.

In other words, the reactive power oscillates between the ac source and the capacitor or reactor, and also between them, at a frequency equals to two times the rated value (50 or 60 Hz). For this reason it can be compensated using VAR generators, avoiding its circulation between the load (inductive or capacitive) and the source, and therefore improving voltage stability of the power system. Reactive power compensation can be implemented with VAR generators connected in parallel or in series. The FACTS are being used for voltage control, reactive/active power flow control, transient and steady-state stabilization that improves the operation and functionality of existing power transmission and distribution system **[37], [38].**

Benefits of Reactive Compensation:

1. Compensation provides economical and quality service aspects.
2. Improves Voltage Profile.
3. Reduces System losses.
4. Reduce lagging component of circuit current.
5. Improve voltage regulation if the capacitor units are properly switched.
6. Increase power factor of the source generators.
7. Decrease kVA loading on the source generators and circuits to relieve an overloaded condition or release capacity for additional load growth.
8. By reducing kVA load on the source generators additional kilowatt loading may be placed on the generators if turbine capacity is available.
9. Reduce demand kVA where power is purchased. Correction to 100 percent Power factor may be economical in some cases.
10. Reduce investment in system facilities per kilowatt of load supplies.

Drawbacks of Reactive Compensation:

1. It introduces resonance when capacitor banks are installed.

2. At the resonant frequency, dangerous amplification to voltages and currents will occur which can cause damage to capacitor banks and other electrical equipment.

2.1 REACTIVE POWER COMPENSATION PRINCIPLE

From above discussed benefits, it is clear that the compensation improves the efficiency of the system. The compensation is done using:

1. Shunt compensation
2. Series compensation

SHUNT COMPENSATION

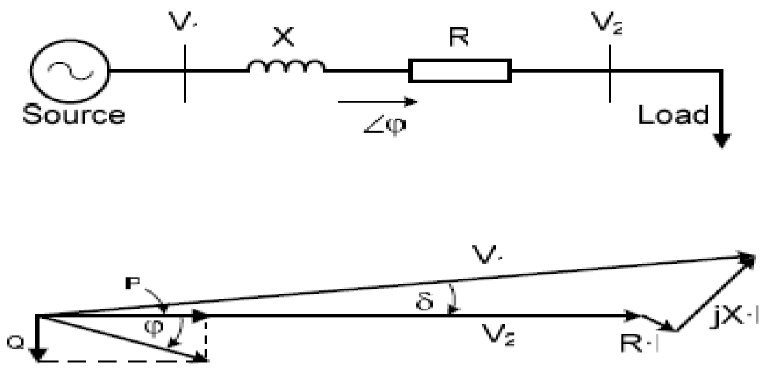
Figure 2.1 shows the principles and theoretical effects of shunt reactive power compensation in a basic ac system, which comprises a source V_1, a power line and a typical inductive load. Figure 2.1-(a) shows the system without compensation, and its associated phasor diagram. In the phasor diagram, the phase angle of the current has been related to the load side, which means that the active current IP is in phase with the load voltage V_2. Since the load is assumed inductive, it requires reactive power for proper operation and hence, the source must supply it, increasing the current from the generator and through power lines. If reactive power is supplied near the load, the line current can be reduced or minimized, reducing power losses and improving voltage regulation at the load terminals. This can be done in three ways:

a) With a capacitor,

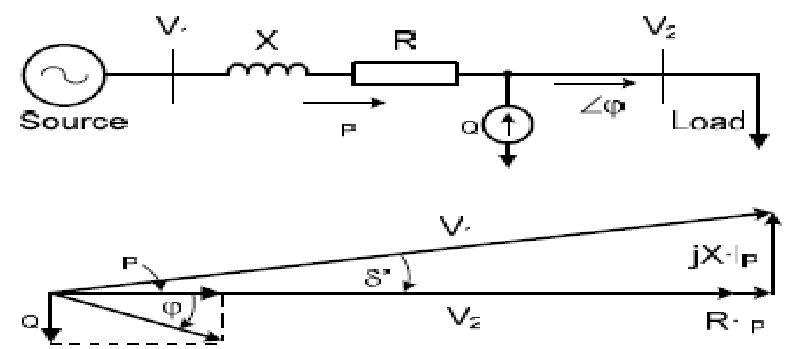
b) With a voltage source,

c) With a current source.

In Figure 2.1-(b), a current source device is being used to compensate the reactive component of the load current (I_Q). As a result, the system voltage regulation is improved and the reactive current component from the source is reduced or almost eliminated. Also a current source or a voltage source can be used for inductive shunt compensation. The main advantages of using voltage or current source VAR generators (instead of inductors or capacitors) is that the reactive power generated is independent of the voltage at the point of connection.



(a)



(b)

FIGURE 2.1. Principles of shunt compensation

(a). Without shunt compensation

(b) Shunt compensation with a current source

SERIES COMPENSATION

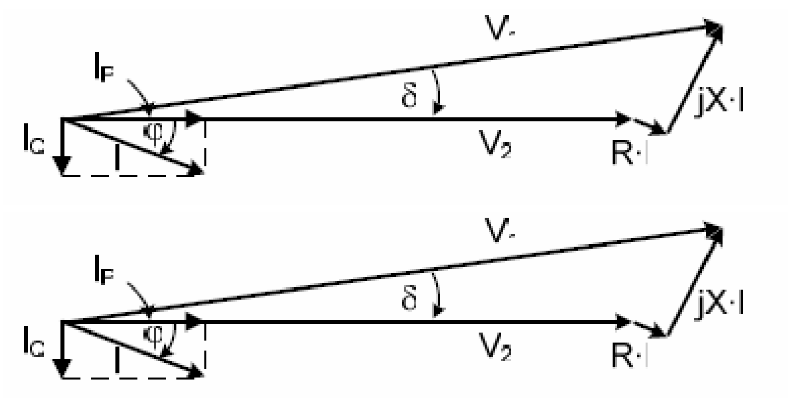
VAR compensation can also be of the series type. Typical series compensation systems use capacitors to decrease the equivalent reactance of a power line at rated frequency. The connection of a series capacitor generates reactive power that, in a self-regulated manner, balances a fraction of the line's transfer reactance. This result is improved functionality of the power transmission system through:-

i) Increased angular stability of the power corridor,

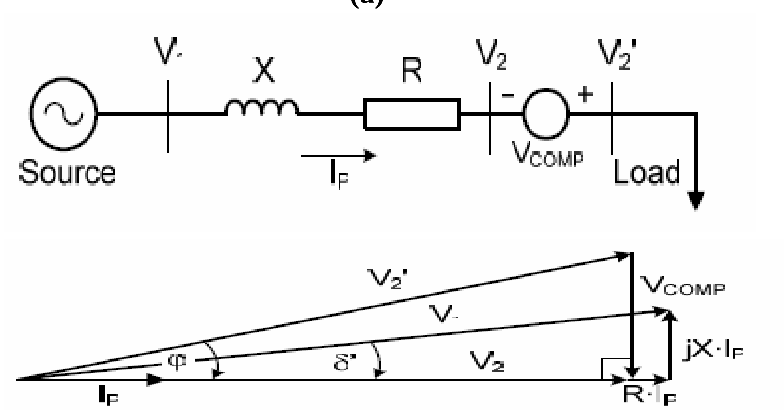
ii) Improved voltage stability of the corridor,

iii) Optimized power sharing between parallel circuits.

Like shunt compensation, series compensation may also be implemented with current or voltage source devices, as shown in Figure. 2.2. The results obtained with the series compensation through a voltage source, which has been adjusted again to have unity power factor operation at V_2 as shown in fig.2.2(b). However, the compensation strategy is different when compared with shunt compensation. In this case, voltage V_{COMP} has been added between the line and the load to change the angle of V_2, which is now the voltage at the load side. With the appropriate magnitude adjustment of V_{COMP}, unity power factor can again be reached at V_2. As it can be seen from the phasor diagram of Figure 2.2(b), V_{COMP} generates a voltage with opposite direction to the voltage drop in the line inductance because it lags the current I_P.



(a)



(b)

Figure.2.2. Principles of series compensation

(a) without compensation

(b). Series compensation with a voltage source

Independent of the source type or system configuration, different requirements have to be taken into consideration for a successful operation of VAR generators. Some of these requirements are simplicity, controllability, dynamics, cost, reliability and harmonic distortion. The following sections describe different solutions used for VAR generation with their associated principles of operation and compensation characteristics.

2.2 THE COMMON COMPENSATION TECHNIQUES

Fixed or Mechanically Switched Capacitors:

Shunt capacitors were first employed for power factor correction in the year 1914 **[16].** The leading current drawn by the shunt capacitors compensates the lagging current drawn by the load. The selection of shunt capacitors depends on many factors, the most important of which is the amount of lagging reactive power taken by the load. In the case of widely fluctuating loads, the reactive power also varies over a wide range. Thus, a fixed capacitor bank may often lead to either over-compensation or under-compensation. Variable VAR compensation is achieved using switched capacitors **[17].** Depending on the total VAR requirement, capacitor banks are switched into or switched out of the system. The smoothness of control is solely dependent on the number of capacitors switching units used. The switching is usually accomplished using relays and circuit breakers. However, these methods based on mechanical switches and relays have the disadvantage of being sluggish and unreliable. And also they generate high inrush currents, and require frequent maintenance **[16].**

SYNCHRONOUS CONDENSERS

Synchronous condensers have played a major role in voltage and reactive power control for more than 50 years. Functionally, a synchronous condenser is simply a synchronous machine connected to the power system. After the unit is synchronized, the field current is adjusted to either generate or absorb reactive power as required by the ac system. The machine can provide continuous reactive power control when used with the proper automatic exciter circuit. Synchronous condensers have been used at both distribution and transmission voltage levels to improve stability and to maintain voltages within desired limits under varying load conditions and contingency situations. However, synchronous condensers are rarely used today because they require substantial foundations and a significant amount of starting and protective equipment. They also contribute to the short circuit current and they cannot be controlled fast enough to compensate for rapid load changes. Moreover, their losses are much higher than those associated with static compensators, and the cost is much higher compared with static compensators. Their advantage lies in their high temporary overload capability **[1].**

THYRISTORIZED VAR COMPENSATORS

As in the case of the synchronous condenser, the aim of achieving fine control over the entire VAR range, has been fulfilled with the development of static compensators (SVC) but with the advantage of faster response times **[6], [7].** Static VAR compensators (SVC) consist of standard reactive power shunt elements (reactors and capacitors) which are controlled to provide rapid and variable reactive power. They can be grouped into two basic categories:

(i). The thyristor-switched capacitor and

(ii). The thyristor-controlled reactor.

i) Thyristor-Switched Capacitors

Figure 2.3 shows the basic scheme of a static compensator of the thyristor-switched capacitor (TSC) type **[16].** The shunt capacitor bank is split up into appropriately small steps, which are individually switched in and out using bidirectional thyristor switches. Each single-phase branch consists of two major parts, the capacitor C and the thyristor switches Sw1 and Sw2. In addition, there is a minor component, the inductor L, whose purpose is to limit the rate of rise of the current through the thyristors and to prevent resonance with the network (normally 6% with respect to Xc). The capacitor may be switched with a minimum of transients if the thyristor is turned on at the instant when the capacitor voltage and the network voltage have the same value. Static compensators of the TSC type have the following properties: stepwise control, average delay of one half a cycle (maximum one cycle), and no generation of harmonics since current transient component can be attenuated effectively **[16], [17].**

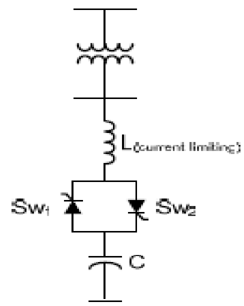


Figure 2.3. The Thyristor switched capacitor configuration.

Despite the attractive theoretical simplicity of the switched capacitor scheme, its popularity has been hindered by a number of practical disadvantages: the VAR compensation is not continuous, each capacitor bank requires a separate thyristor switch and therefore the construction is not economical, the steady state voltage across the non-conducting thyristor switch is twice the peak supply voltage, and the thyristor must be rated for or protected by external means against line voltage transients and fault currents.

An attractive solution to the disadvantages of using TSC is to replace one of the thyristor switches by a diode. In this case, inrush currents are eliminated when thyristors are fired at the right time, and a more continuous reactive power control can be achieved if the rated power of each capacitor bank is selected following a binary combination, as described in **[13]** and **[18].** This configuration is shown in Figure.2.4. In this figure, the inductor L_{min} is used to prevent any inrush current produced by a firing pulse out of time.

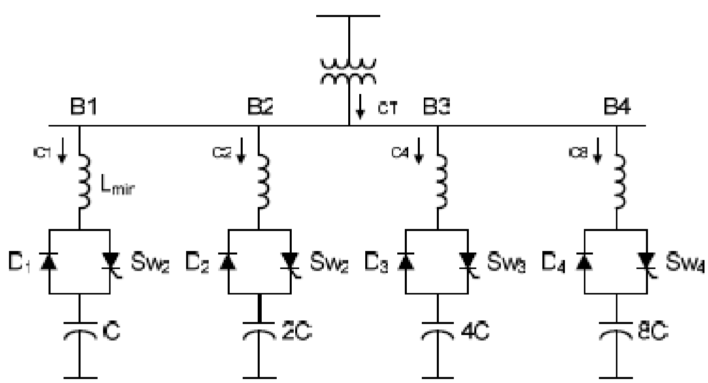


Figure 2.4. Binary Thyristor diode switched capacitor compensation.

ii) Thyristor-Controlled Reactor

Figure 2.5 shows the scheme of a static compensator of the thyristor controlled reactor (TCR) type. In most cases, the compensator also includes a fixed capacitor and a filter for low order harmonics, which is not show in this figure. Each of the three phase branches includes an inductor L, and the thyristor switches Sw1 and Sw2. Reactors may be both switched and phase-angle controlled **[20], [21], [22].** When phase-angle control is used, a continuous range of reactive power consumption is obtained. It results, however, in the generation of odd harmonic current components during the control process. Full conduction is achieved with a gating angle of 90°. Partial conduction is obtained with gating angles between 90° and 180°, by increasing the thyristor gating angle, the fundamental component of the current reactor is reduced. This is equivalent to increase the inductance, reducing the reactive power absorbed by the reactor. However, it should be pointed out that the change in the reactor current may only take place at discrete points of time, which means that adjustments cannot be made more frequently than once per half-cycle. Static compensators of the TCR type are characterized by the ability to perform continuous control, maximum delay of one half cycle and practically no transients. The principal disadvantages of this configuration are the generation of low frequency harmonic current components, and higher losses when working in the inductive region (i.e. absorbing reactive power) **[20].**

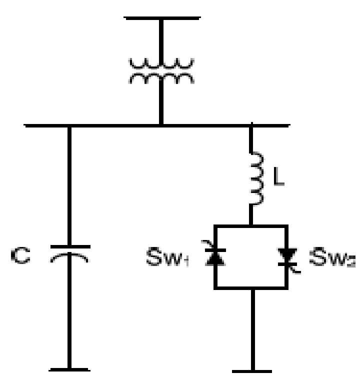


Figure 2.5. Thyristor controlled reactor configuration.

iii) Combined TSC and TCR

Irrespective of the reactive power control range required, any static compensator can be built up from one or both of the above mentioned schemes (i.e. TSC and TCR), as shown in Figure.2.6. In those cases where the system with switched capacitors is used, the reactive power is divided into a suitable number of steps and the variation will therefore take place stepwise. Continuous control may be obtained with the addition of a thyristor-controlled reactor. If it is required to absorb reactive power, the entire capacitor bank is disconnected and the equalizing reactor becomes responsible for the absorption. By coordinating the control between the reactor and the capacitor steps, it is possible to obtain fully step less control. Static compensators of the combined TSC and TCR type are characterized by a continuous control, practically no transients, low generation of harmonics (because the controlled reactor rating is small compared to the total reactive power), and flexibility in control and operation.

An obvious disadvantage of the TSC-TCR as compared with TCR and TSC type compensators is the higher cost. A smaller TCR rating results in some savings, but these savings are more than absorbed by the cost of the capacitor switches and the more complex control system **[16].**

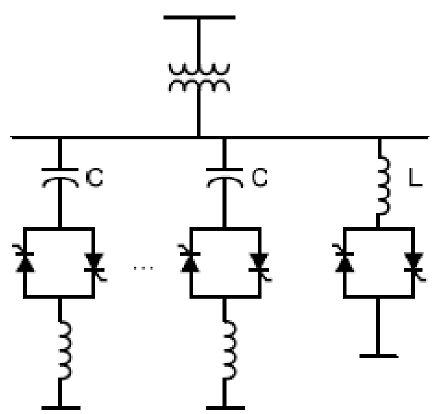


Figure 2.6 Combine TSC and TCR configuration

To reduce transient phenomena and harmonics distortion, and to improve the dynamics of the compensator, some researchers have applied self commutation to TSC and TCR. Some examples of this can be found in **[21], [22].** However, best results have been obtained using self-commutated compensators based on conventional two-level and three-level inverters.

iv) Thyristor Controlled Series Compensation

Figure 2.7 shows a single line diagram of a Thyristor Controlled Series Compensator (TCSC). TCSC provides a proven technology that addresses specific dynamic problems in transmission systems. TCSC's are an excellent tool to introduce if increased damping is required when interconnecting large electrical systems. Additionally, they can overcome the problem of Sub synchronous Resonance (SSR), a phenomenon that involves an interaction between large thermal generating units and series compensated transmission systems.

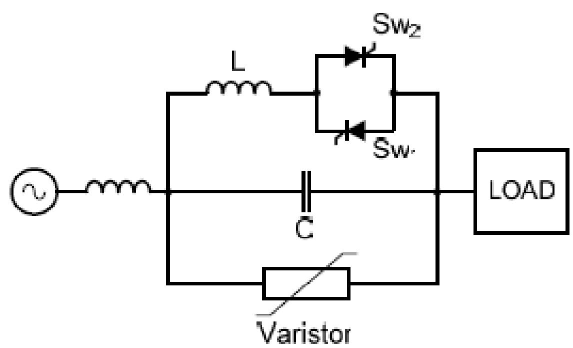


Figure 2.7. Power circuit topology of a thyristor controlled series compensator

There are two bearing principles of the TCSC concept.:

(i). the TCSC provides electromechanical damping between large electrical systems by changing the reactance of a specific interconnecting power line, i.e. the TCSC will provide a variable capacitive reactance.

(ii). the TCSC shall change its apparent impedance (as seen by the line current) for sub synchronous frequencies such that a prospective sub synchronous resonance is avoided.

Both these objectives are achieved with the TCSC using control algorithms that operate concurrently. The controls will function on the thyristor circuit (in parallel to the main capacitor bank) such that controlled charges are added to the main capacitor, making it a variable capacitor at fundamental frequency but a "virtual inductor" at sub synchronous frequencies. For power oscillation damping, the TCSC scheme introduces a component of modulation of the effective reactance of the power transmission corridor. By suitable system control, this modulation of the reactance is made to counteract the oscillations of the active power transfer, in order to damp these out.

FACTS DEVICES:

As new technology for power transmission system, FACTS controllers not only provide the same benefits as conventional compensators with mechanically-controlled switches in steady state but also improve the dynamic and transient performance of the power system. The power electronics-based switches in the functional blocks of FACTS can usually be operated repeatedly and the switching time is a portion of a periodic cycle, which is much shorter than the conventional mechanical switches. The advance of semiconductors increases the switching frequency and voltage-ampere ratings of the solid switches and facilitates the applications **[41].** FACTS controllers have many configurations. In general, they can be categorized into

(i). Shunt-connected controllers,

(ii). Series-connected controllers and their

(iii). Combinations.

(i). Shunt-connected controllers

FACTS controllers can be impedance type, based on thyristors without gate turn-off capability, which are called Static Var Compensator (SVC) for shunt-connected application. Another type of FACTS controllers is converter-based which is usually in the form of a Static Synchronous Compensator (STATCOM).

- **Static Var Compensator (SVC)**

Static Var Compensator is “a shunt-connected static Var generator or absorber whose output is adjusted to exchange capacitive or inductive current so as to maintain or control specific parameters of the electrical power system (typically bus voltage)” **[42].** SVC is based on thyristors without gate turn-off capability. The operating principal and characteristics of thyristors realize SVC variable reactive impedance. SVC includes two main components and their combination: (1) Thyristor-controlled and Thyristor-switched Reactor (TCR and TSR); and (2) Thyristor-switched capacitor (TSC). In Figure 2.8 shows the diagram of SVC.

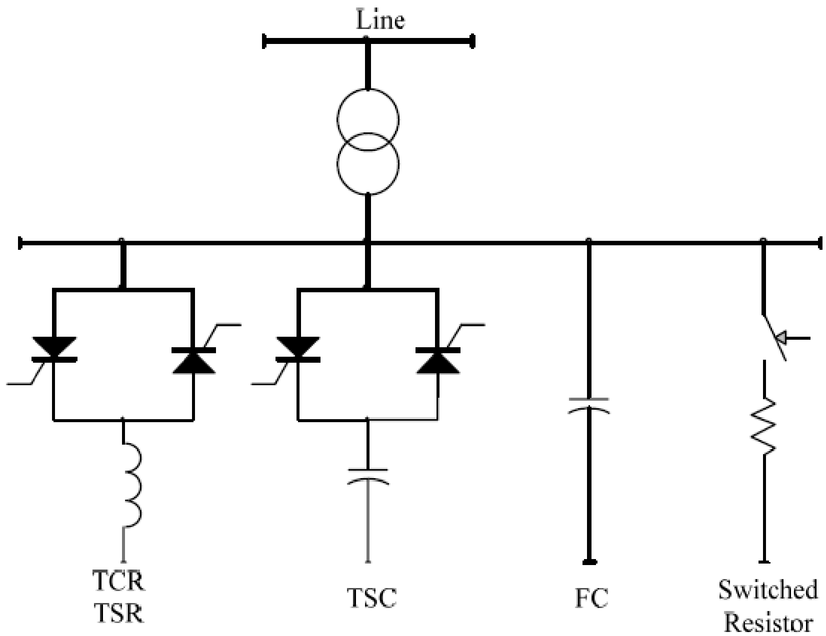


Figure 2.8. Static VAR Compensators (SVC): TCR/TSR, TSC, FC and Mechanically Switched Resistor

TCR and TSR are both composed of a shunt-connected reactor controlled by two parallel, reverse-connected thyristors. TCR is controlled with proper firing angle input to operate in a continuous manner, while TSR is controlled without firing angle control which results in a step change in reactance.

TSC shares similar composition and same operational mode as TSR, but the reactor is replaced by a capacitor. The reactance can only be either fully connected or fully disconnected zero due to the characteristic of capacitor.

With different combinations of TCR/TSR, TSC and fixed capacitors, a SVC can meet various requirements to absorb/supply reactive power from/to the transmission line.

- **Converter-based Compensator**

Static Synchronous Compensator (STATCOM) is one of the key Converter-based Compensators which are usually based on the voltage source inverter (VSI) or current source inverter (CSI), as shown in Figure 2.9(a). Unlike SVC, STATCOM controls the output current independently of the AC system voltage, while the DC side voltage is automatically maintained to serve as a voltage source. Mostly, STATCOM is designed based on the VSI.

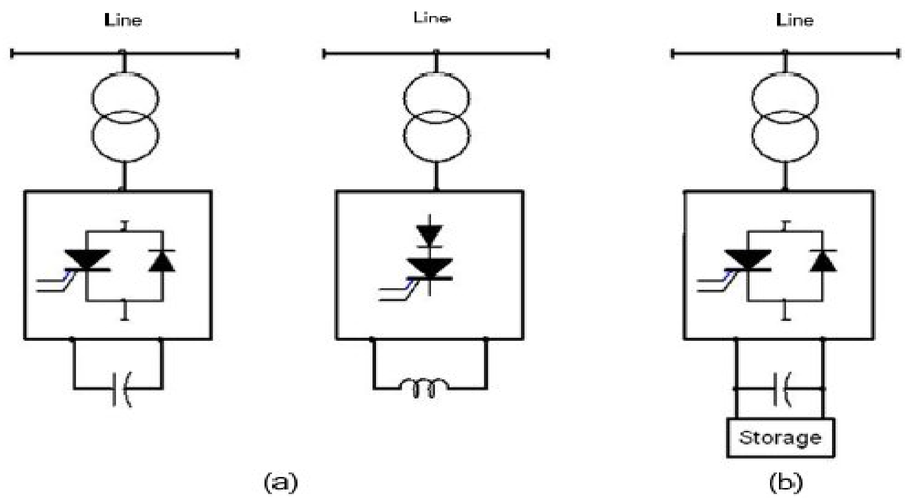


Figure 2.9. STATCOM topologies: (a) STATCOM based on VSI and CSI (b) STATCOM with storage

Various combinations of the switching devices and appropriate topology make it possible for a STATCOM to vary the AC output voltage in both magnitude and phase. Also, the combination of STATCOM with a different storage device or power source (as shown in Figure 2.9(b)) endows the STATCOM the ability to control the real power output. STATCOM has much better dynamic performance than conventional reactive power compensators like SVC. The gate turn-off ability shortens the dynamic response time from several utility period cycles to a portion of a period cycle. STATCOM is also much faster in improving the transient response than a SVC. This advantage also brings higher reliability and larger operating range. Figure 2.6 shows the V-I characteristics of STATCOM and SVC **[42].**

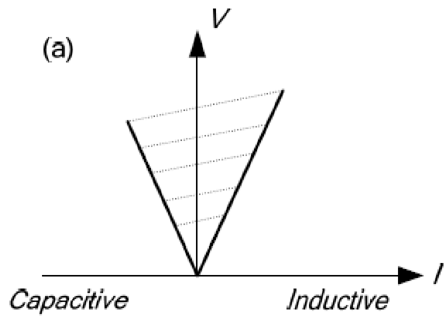


Figure 2.10. V-I characteristics of SVC and STATCOM: (a) SVC; (b) STATCOM

(ii). Series-connected controllers

As shunt-connected controllers, series-connected FACTS controllers can also be divided into either impedance type or converter type. The former includes Thyristor-Switched Series Capacitor (TSSC), Thyristor-Controlled Series Capacitor (TCSC), Thyristor-Switched Series Reactor, and Thyristor-Controlled Series Reactor. The latter, based on VSI, is usually in the form of a Static Synchronous Series Compensator (SSSC). The composition and operation of different types are similar to the operation of the shunt-connected peers.

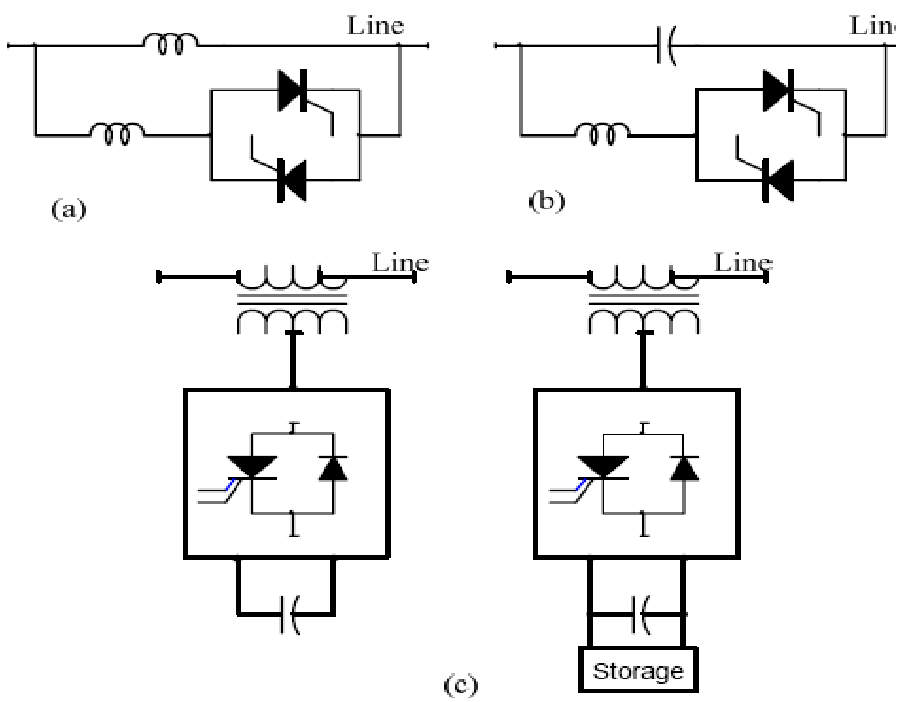


Figure 2.11. Series-connected FACTS controllers: (a) TCSR and TSSR; (b) TSSC; (c) SSSC

CHAPTER- 3

PROBLEM FORMULATION USING GENETIC ALGORITHM

In this, GA is briefly reviewed and the formulation of problem is discussed.

3.1 GENETIC ALGORITHM STRUCTURE

Genetic Algorithms are search mechanisms based on the Darwinian principle of natural evolution. Genetic Algorithms are search mechanisms based on natural selection and natural genetics. They operate on the law of coincidence, which takes advantage of pre-information in order to derive improvement from it. Genetic Algorithms used for optimization are based on the principle of biological evolution. They are very different to many conventional methods in the sense that they simultaneously consider many possible solutions to the problem. By considering many points in the search space, the algorithm simultaneously reduces the chance of getting trapped at a local minimum. They are the result of research done to incorporate the adaptive process of natural systems into design of artificial systems. GAs are computationally simple and provide robust search in complex problem spaces" **[26].** They work not with the parameters themselves but with a string of numbers representing the parameter set. Genetic Algorithms use a set of probabilistic rules in order to guide their search.

ADVANTAGES OF GA

The advantages associated with a Genetic Algorithm are **[2, 3]**

1. Ease of implementation.
2. Differentiability of the objective function is not required.
3. Can handle complex, multi-nodal optimization problems.
4. Computational simplicity.
5. Power-full search ability to attain the global optimum.
6. Extremely robust with respect to the complexity of the problem.

7. Diversity of solutions is maintained with mutation.

8. Takes into account the overall effect on the system.

DISADVANTAGES OF GA

The disadvantages associated with the use of a Genetic Algorithm are **[2, 4]**

1. Relatively complex when it comes to incorporating the algorithm into a software program.

2. Relatively large computational time and effort.

3. Premature convergence problems.

The process of GA follows this pattern **[10].**

1. An initial population of a random solution is created.

2. Each member of the population is assigned a fitness value based on its evaluation against the current problem.

3. Solution with highest fitness value is most likely to parent new solutions during reproduction.

4. The new solution set replaces the old, a generation is completed and the process continues at step (2).

Members of the population (chromosomes) are represented by a string of genes. Each gene represents a design variable and is symbolized by a binary number. Then, GA operators are used which are:

- reproduction,
- crossover and
- Mutation.

This simple genetic procedure constantly produces even fitter offspring through successive generations. This process gradually leads the search towards a global optimum solution **[10].** It involves nothing more than swapping of genes and string cloning. This allows GA to produce good results in circumstances which are hard to achieve through many conventional methods. The further attraction to such an algorithm is that it is extremely robust with respect to the complexity of the problem **[10]**. A flowchart for a GA is shown in fig.3.1.

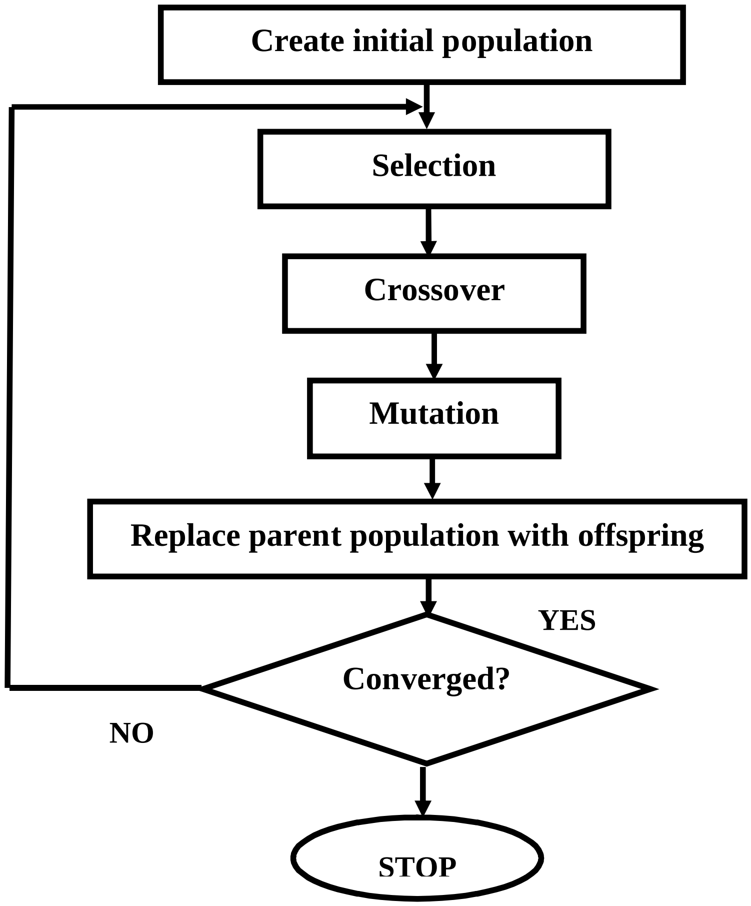


Figure 3.1. Typical flowchart of genetic algorithm

GA work iteratively sustaining a set (population) of representative chromosomes of possible solutions to the problem domain at hand. As an optimization method, they evaluate and manipulate these chromosomes using stochastic evolution rules called Genetic Operators. During each iterative step, known as a generation, the representative chromosomes in the current population are evaluated for their fitness as optimal solutions. By comparing these fitness values, a new population of solution chromosomes is created using the genetic operators, known as reproduction, crossover and mutation. **[26]**. There are six components that are needed to implement a Genetic Algorithm.

These six components listed below and are detailed in the following sections:

1. Representation
2. Initialization
3. Evaluation Function
4. Genetic Operators, and
5. Genetic Parameters
6. Termination

1. REPRESENTATION

Genetic Algorithms are derived from a study of biological systems. In biological systems evolution takes place on organic devices used to encode the structure of living beings. These organic devices are known as chromosomes. A living being is only a decoded structure of the chromosomes. Natural selection is the link between chromosomes and the performance of their decoded structures. In GA, the design variables or features that characterize an individual are represented in an ordered list called a string. Each design variable corresponds to a gene and the string of genes corresponds to a chromosome.

Encoding

The application of a genetic algorithm to a problem starts with the encoding. The encoding specifies a mapping that transforms a possible solution to the problem into a structure containing a collection of decision variables that are relevant to the problem. A particular solution to the problem can then be represented by a specific assignment of values to the decision variables. The set of all possible solutions is called the search space and a particular solution represents a point in that search space. In practice, these structures can be represented in various forms, including among others, strings, trees, and graphs. There are also a variety of possible values that can be assigned to the decision variables, including binary, k-array, and permutation values.

Traditionally, genetic algorithms have used mostly string structures containing binary decision variables. The binary coding is used in solving all the problems discussed in the dissertation. The terminology used in GAs is borrowed from real genetics. The structure that encodes a solution is called a chromosome or individual. A decision variable is called a gene and its value is called allele.

2. INITIALIZATION

Genetic Algorithms operate with a set of strings instead of a single string. This set of strings is known as a population and is put through the process of evolution to produce new individual strings. To start with, the initial population could be made up of chromosomes chosen at random or based on heuristically selected strings. In whichever case, the initial population should contain a wide variety of structures **[26].** The number of chromosomes in a population is usually selected to be between 30 and 100 **[11].**

3. EVALUATION FUNCTION

The evaluation function is a procedure for establishing the fitness of each chromosome in the population and is very much application orientated. Since Genetic Algorithms proceed in the direction of evolving the fittest chromosomes, and the performance is highly sensitive to the fitness values. In the case of optimization routines, the fitness is the value of the objective function to be optimized. Penalty functions can also be incorporated into the objective function, in order to achieve a constrained problem **[26].**

Fitness function

The Genetic algorithm is based on Darwin's principle that "The candidates, which can survive, will live, others would die". This principal is used to find fitness value of the process for solving maximization problems. Minimization problems are usually transferred into maximization problems using some suitable transformations. Fitness value $f(x)$ is derived from the objective function and is used in successive genetic operations. The fitness function for maximization problem can be used the same as objective function $F(X)$.

Coming up with an encoding is the first thing in genetic algorithm user has to do. The next step is to specify a function that can assign a score to any possible solution or structure. The score is a numerical value that indicates how well the particular solution solves the problem. Using a biological metaphor, the score is the fitness of the individual solution. It represents how well the individual adapts to the environment. In case of optimization, the environment is the search space. The task of the GAs is to discover solutions that have fitness values among the set of all possible solutions.

In general, a fitness function F(x) is first derived from the objective function and used in successive genetic operations. Certain genetic operators require that the fitness function be non-negative. For maximization problems, the fitness function be considered to be the same as objective function or

$$F(X) = f(X)$$

For minimization problems, the fitness function is an equivalent maximization problem chosen such that the optimum point remains unchanged. The following fitness function is often used in minimization problems:

$$F(x) = 1/(1 + f(X))$$

This information does not alter the location of the minimum, but converts a minimization problem to an equivalent maximization problem. The fitness function value of a string is known as the string's fitness. The operation of GAs begins with a population of random strings representing design or decision variables. Thereafter, each string is evaluated to find the fitness value. The population is then operated by three operators- reproduction, crossover, and mutation to create a new population of points. The new population is further evaluated and tested for termination. If the termination criteria is not met, the population is iteratively operated by the above three operators and evaluated. This procedure is continued until the termination criterion is met. One cycle of these operations and the subsequent evaluation procedure is known as a generation in GA's terminology.

4. GENETIC OPERATORS

Genetic operators are a set of random transition rules employed by a Genetic Algorithm. These operators are applied to a randomly chosen set of chromosomes during each generation, to produce a new and improved population from the old one. A simple GA consists of three basic operators **[26]:**

- reproduction,
- crossover,
- mutation.

***Reproduction**:*

Reproduction is a random selection process based on the rules of probability, in which chromosomes are selected to produce offspring based on their fitness values. This will ensure that the expected number of times a chromosome is chosen is proportional to its fitness, relative to the rest of the population. Strings with higher fitness values are more likely to contributing offspring, and are simply copied on into the next generation **[26]**. Reproduction is usually first operator applied on a population. Reproduction selects good strings in a population and forms a mating pool. That is why the reproduction operator is sometimes known as the selection operator. There exist a number of reproduction operators in GA literature, but essential idea in all of them is that the above average strings are picked from the current population and their multiple copies are inserted in the mating pool in a probabilistic manner. The commonly used reproduction operator is the proportionate reproduction operator where a string is selected for the mating pool with a probability proportional to its fitness. Thus, the i^{th} string in the population is selected with a probability proportional to fitness F_i. Since the population size is usually kept fixed in a simple GA, the sum of the probability of each string being selected for the mating pool must be one. Therefore, the probability for selecting the i^{th} string is:

$$P_i = F_i / \sum_{i=1}^{n} F_i$$

Where n is the population size.

One way to implement this selection scheme is to imagine a roulette-wheel with its circumference marked for each string proportionate to the string's fitness. The roulette-wheel is spun n times, each time selecting an instance of the string chosen by a roulette-wheel pointer. Since the circumference of the wheel is marked according to a string's fitness, this roulette-wheel mechanism is expected to make f_i / f_{av} copies of the i^{th} string in the mating pool. The average fitness of the population is calculated as:

$$f_{av} = \left(\sum_{i=1}^{n} f_i\right) \times \frac{1}{n}$$

Figure (3.2) shows a roulette-wheel for five individuals having different fitness values. Since the third individual has a higher fitness value than any other, it is expected that the Roulette-wheel selection will choose the third individual more than any other individual. This roulette-wheel selection scheme can be simulated easily.

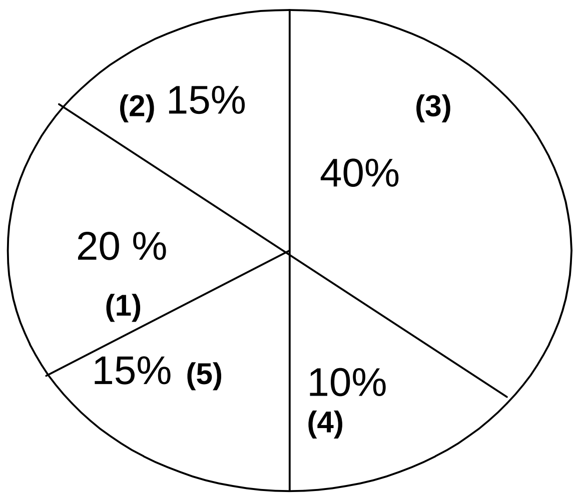


Figure 3.2. Roulette Wheel Selection

Using the fitness value F_i of all the strings, the probability of selecting a string p_i can be calculated. Thereafter the cumulative probability (P_i) of each string being copied can be calculated by adding the individual probabilities from the top of the list. Thus, the bottom-most string in the population should have a cumulative probability (P_n) equal to one. The roulette-wheel concept can be simulated by realizing that the i^{th} string in the population represents the cumulative probability values from P_{i-1} to P_i. The first string represents the cumulative value from zero to P_1. Thus, the cumulative probability of any string lies between 0 to 1. In order to choose n strings, n random numbers between zeros to one are created at random. Thus, a string that represents the chosen random number in the cumulative range (calculated from the fitness value) for the string is copied to the mating pool. This way, the string with a higher fitness value will represent a larger range in the cumulative probability values and therefore has a higher probability of being copied into the mating pool. On the other hand, a string with a smaller fitness value will represent a smaller range in the cumulative probability values and has a smaller probability of being copied into the mating pool.

Crossover

The basic operator for producing new chromosome in the genetic algorithm is crossover. In the crossover operator, information is exchanged among strings of the mating pool to create new strings. In other words, crossover produces new individuals that have some parts of both parent's genetic materials. It is expected from the crossover operator that good substrings from the parent strings will be combined to form a better child offspring. At the molecular level what occurs is that a pair of Chromosomes bump into one another, exchange chunks of genetic information and drift apart. This is the recombination operation, which GA generally refers to as crossover because of the way that genetic material crosses over from one chromosome to another. The crossover operation happens in an environment, where the selection of who gets to mate is a function of the fitness of the individuals. How good the individual is at competing in its environment.

Some Genetic Algorithms use a simple function of the fitness measure to select individuals (probabilistically) to undergo genetic operations such as crossover or asexual reproduction (the propagation of genetic material unaltered). This is fitness-proportionate selection. Other implementations use a model in which certain randomly selected individuals in a subgroup compete and the fittest is selected. This is called tournament selection and is the forms of selection we see in nature .The two processes that most contribute to evolution are crossover and fitness based selection/reproduction

There are three forms of crossover:
(1) one point crossover,
(2) multipoint crossover, and
(3) uniform crossover.

(1). One point crossover : Two individual strings are selected at random from the mating pool. Next, a crossover site is selected randomly along the string length and binary digits (alleles) are swapped (exchanged) between the two strings at the crossover site.

Parent 1: x_1 = {010 **1101011**}

Parent 2: x_2 = {100 **0011100**}

Suppose site **3** is selected at random. It means starting from the 4th bit and onwards, bits of strings will be swapped to produce offspring which are given below;

Offspring 1: x_1 = {010 **0011100**}

Offspring 2: x_2 = {100 **1101011**}

(2). Multipoint crossover : For multipoint crossover, from m crossover positions along the string length, l are chosen at random with no duplicates and sorted into ascending order.

$$k_i \;€\{1,2,\ldots,l-1]$$

Where

k_i is the ith crossover point

l is the length of the chromosome.

The bits between successive crossover points are exchanged alternatively between two parents to give two new offspring.

Parent 1: x_1 = {000 **000** 000 **000**}

Parent 2: x_2 = {111 **111** 111 **111**}

Suppose k € {3, 6, 9} is selected at random. It means the bits 4th, 5th, 6th are exchanged, bits 7th, 8th, and 9th of parent string are not exchanged and bits 10th, 11th, and12th of parent string are exchanged to produce offspring.

Offspring 1: x_1 = {000 **111** 000 **111**}

Offspring 2: x_2 = {111 **000** 111 **000**}

(3). Uniform crossover: Single and multipoint crossovers define cross points as places within length of the string where a chromosome can be split. Uniform crossover generalizes this scheme to make every locus a potential crossover point. A crossover mask having same length as the chromosome structure is created at random and the parity of the bits in the mask indicates which parent will supply the offspring with which bits. The '1' in the random mask means bits swapping and the '0' means bit replicating.

Mutation

Mutation also plays a role in this process, although how important its role is, depends upon the conditions. It is also known as background operator .It plays dominant role in the evolutionary process. It cannot be stressed too strongly that the genetic Algorithm is not a random search for a solution to a problem for highly fit individual.

The genetic algorithm uses stochastic processes, but the result is distinctly non-random. Genetic Algorithms are used for a number of different applications areas. An example of this would be multidimensional optimization problems in which the character string of the Chromosome can be used to encode the values for the different parameters being optimized.

Mutation is an important operator, as newly created individuals have no new inheritance information, this process results in contraction of the population at one single point, which is wished one. Mutation operator changes 1 to 0 at only one place in the whole string with a small probability and vice versa.

e.g. Child 1 1011**0**0

Let mutation is done at location 5 the new child will be

New child 1011**1**0

In general, the mutation probability is fixed through out the whole process. However a small mutation probability results in small premature convergence but the search with large fixed mutation probability will not converge a lot so this operator is seldom used in the process. It is not a primary operator but it ensures that the probability of searching any region in the problem space is never zero. This prevents complete loss of genetic material through reproduction and crossover **[26].**

5. GENETIC PARAMETERS

Genetic parameters are a means of manipulating the performance of a Genetic Algorithm. There are many possible implementations of Genetic Algorithms involving variations such as additional genetic operators, variable sized populations and so forth. Listed below are some of the basic genetic parameters used by researchers to tune the performance of Genetic Algorithms **[26].**

i) Population Size (N): Population size affects the efficiency and performance of the algorithm. Using a small population size may result in a poor performance from the algorithm. This is due to the process not covering the entire problem space. A larger population on the other hand, would cover more space and prevent premature convergence to local minima. At the same time, a large population needs more evaluations per generation and may slow down the convergence rate **[26].**

ii) Crossover rate (C): The crossover rate is the parameter that affects the rate at which the process of crossover is applied. In each new population, the number of strings that undergo the process of crossover can be depicted by a chosen probability. This probability is known as the crossover rate. A higher crossover rate introduces new strings more quickly into the population. If the crossover rate is too high, high-performance strings are eliminated faster than selection can produce improvements. A low crossover rate may cause stagnations due to the lower exploration rate, and convergence problems may occur **[26]**.

iii) Mutation rate (M): Mutation rate is the probability with which each bit position of each chromosome in the new population undergoes a random change after the selection process. It is basically a secondary search operator which increases the diversity of the population. A low mutation rate helps to prevent any bit position from getting trapped at a single value, whereas a high mutation rate can result in essentially random search **[26]**.

6. TERMINATION

This generational process is repeated until a termination condition has been reached. Common terminating conditions are:

1. A solution is found that satisfies minimum criteria
2. Fixed number of generations reached
3. Allocated budget (computation time/money) reached
4. The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results
5. Manual inspection
6. Combinations of the above.

3.2. CAPACITOR PLACEMENT AND SIZING USING G.A

In order to solve the problem of optimal placement and sizing of shunt capacitor banks in a transmission system, GA is used. GA start with a diverse population of potential solution, which allows for the exploration of many different optimums in parallel. By doing this the probability of the solution getting stuck at a local optimum is reduced considerably.

The selected transmission system for performing the Genetic Algorithm is an 30-bus transmission **[27].**

3.2.1 IEEE 30-BUS TRANSMISSION SYSTEM STRUCTURE

This transmission system was considered by many researchers to demonstrate the effectiveness of capacitor placement. A single line diagram of system is fig.3.3. this system consists of two generator buses 1 and 2 in which 1 is the slack bus. In this system tap changers are also used as shown in figure3.3. Tap changers are placed on bus no. **4, 6, 9, 10, 11, 12, 13, 27, and 28**. Remaining buses are load buses. Details of the bus data and line data characteristics are shown below in Tables 3.1 and 3.2, respectively.

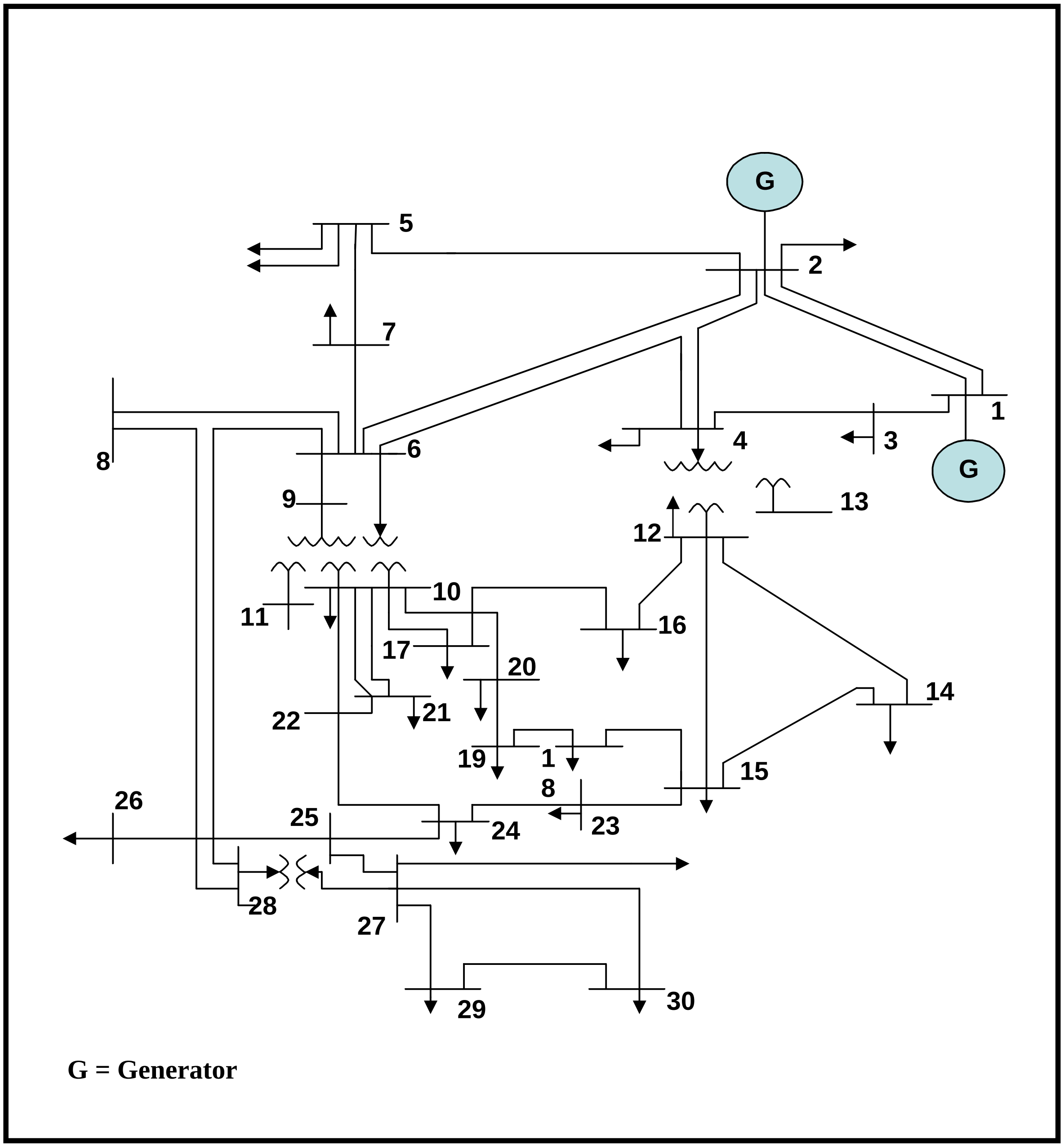


Figure 3.3. Single line diagram of 30 bus transmission system.

3.2.2 BUS DATA

Table 3.1 below displays the bus data characteristics of the transmission system discussed above. Column 1 of Table 3.1 outlines the bus number and column 2 contains the bus code. Columns 3 and 4 show the voltage magnitudes in p.u. and phase angle in degrees. Columns 5 and 6 outline the size of the active and reactive loads connected to the corresponding buses in MW and MVAR. Columns 7 through to 10 are MW, MVAR, minimum MVAR and maximum MVA of generation, in that order. The last column is the injected MVAR of capacitance into the system. The bus code entered in column 2 is used for identifying load, voltage-controlled, and slack buses as outlined below;

1 – This code is used for the slack bus.
0 – This code is used for load buses.
2 – This code is used for the voltage controlled buses.

3.2.3 LINE DATA

Table 3.2 below displays the line data characteristics of the transmission system discussed above. Columns 1 and 2 of Table 3.2 outline the corresponding line bus numbers. Columns 3 through to 5 contain the line resistance, reactance, and one-half of the total line charging susceptance in per unit on the MVA base of 100MVA. The last column details the transformer tap setting. The bus and line data was structured in such a way so that the MATLAB load flow program of **[2]** could be used for the simulation.

Bus data

IEEE 30-BUS TEST SYSTEM (American Electric Power)

Bus No	Bus code	Voltage Mag.	Angle Degree	-----Load----- MW	MVAR	--------Generator-------- MW	MVAR	Q_{min}	Q_{max}	Injected MVAR
[1	1	1.06	0.0	0.0	0.0	0.0	0.0	0	0	0
2	2	1.043	0.0	21.70	12.7	40	0.0	-40	50	0
3	0	1.0	0.0	2.4	1.2	0.0	0.0	0	0	0
4	2	1.06	0.0	7.6	1.6	0.0	0.0	0	0	0
5	2	1.01	0.0	94.2	19.0	0.0	0.0	-40	40	0
6	2	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
7	0	1.0	0.0	22.8	10.9	0.0	0.0	0	0	0
8	2	1.01	0.0	30.0	30.0	0.0	0.0	-10	40	0
9	2	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
10	2	1.0	0.0	5.8	2.0	0.0	0.0	0	0	0
11	2	1.082	0.0	0.0	0.0	0.0	0.0	-6	24	0
12	2	1.0	0	11.2	7.5	0	0	0	0	0
13	2	1.071	0	0	0.0	0	0	-6	24	0
14	0	1	0	6.2	1.6	0	0	0	0	0
15	0	1	0	8.2	2.5	0	0	0	0	0
16	0	1	0	3.5	1.8	0	0	0	0	0
17	0	1	0	9.0	5.8	0	0	0	0	0
18	0	1	0	3.2	0.9	0	0	0	0	0
19	0	1	0	9.5	3.4	0	0	0	0	0
20	0	1	0	2.2	0.7	0	0	0	0	0
21	0	1	0	17.5	11.2	0	0	0	0	0
22	0	1	0	0	0.0	0	0	0	0	0
23	0	1	0	3.2	1.6	0	0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	0
25	0	1	0	0	0.0	0	0	0	0	0
26	0	1	0	3.5	2.3	0	0	0	0	0
27	2	1	0	0	0.0	0	0	0	0	0
28	2	1	0	0	0.0	0	0	0	0	0
29	0	1	0	2.4	0.9	0	0	0	0	0
30	0	1	0	10.6	1.9	0	0	0	0	0];

***TABLE 3.1*. BUS DATA for 30 bus transmission system.**

Line data

Bus nl	Bus nr	R p.u.	X p.u.	1/2 B p.u.	1 for line code or tap setting at bus nl
[1	2	0.0192	0.0575	0.02640	1
1	3	0.0452	0.1852	0.02640	1
2	4	0.0570	0.1737	0.01840	1
3	4	0.0132	0.0379	0.00420	1
2	5	0.0472	0.1983	0.02090	1
2	6	0.0581	0.1763	0.01870	1
4	6	0.0119	0.0414	0.00450	1
5	7	0.0460	0.1160	0.01020	1
6	7	0.0267	0.0820	0.00850	1
6	8	0.0120	0.0420	0.00450	1
6	9	0.0	0.2080	0	0.978
6	10	0	0.5560	0	0.969
9	11	0	0.2080	0	1
9	10	0	0.1100	0	1
4	12	0	0.2560	0	0.932
12	13	0	0.1400	0	1
12	14	0.1231	0.2559	0	1
12	15	0.0662	0.1304	0	1
12	16	0.0945	0.1987	0	1
14	15	0.2210	0.1997	0	1
16	17	0.0824	0.1923	0	1
15	18	0.1073	0.2185	0	1
18	19	0.0639	0.1292	0	1
19	20	0.0340	0.0680	0	1
10	20	0.0936	0.2090	0	1
10	17	0.0324	0.0845	0	1
10	21	0.0348	0.0749	0	1
10	22	0.0727	0.1499	0	1
21	22	0.0116	0.0236	0	1
15	23	0.1000	0.2020	0	1
22	24	0.1150	0.1790	0	1
23	24	0.1320	0.2700	0	1
24	25	0.1885	0.3292	0	1
25	26	0.2544	0.3800	0	1
25	27	0.1093	0.2087	0	1
28	27	0	0.3960	0	0.968
27	29	0.2198	0.4153	0	1
27	30	0.3202	0.6027	0	1
29	30	0.2399	0.4533	0	1
8	28	0.0636	0.2000	0.0214	1
6	28	0.0169	0.0599	0.065	1];

TABLE.3.2 LINE DATA for 30 bus transmission line

3.3 GA STRUCTURE USED TO SOLVE PROBLEM

Structure of Chromosomes:

In this thesis, the chromosome structure for the proposed Genetic Algorithm consists of popsize = 50, i.e. 50 chromosomes each have 17 decimal numbers as substring as shown in Table 3.3. Popsize represents the number of possible solutions or generated chromosomes for shunt capacitor placement in the entire transmission system. The decimal numbers indicate the **size** of the installed capacitors at the bus under consideration.

The selected number buses of possible compensation (candidate) for shunt capacitor placement is N=17. These busses are selected as load buses of system. We can also select busses randomly in case where there would be no need to install capacitors on all load busses. To select busses for capacitor placement, randomly following steps are to be followed.

1. To select busses we generate an array which only includes load busses in the system.

2. In this array there were no generator buses and slack buses, only load buses are selected for this pool. In our problem this array consists of 17 numbers of busses shown in TABLE 3.4

3. Then we generate a set of 17 different random numbers consists of 0s and 1s. There would be 8 numbers of 1s and rest of them would be 0s if requirement is to select 8 buses

4. Now the random location at which 1 takes place would be the location of bus to be selected from the array of 17 load buses, which are 3,16,17,19,21,24,25,26 as shown in Table 3.3

Load buses	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Selected bus	**1**	**0**	**0**	**0**	**1**	**1**	**0**	**1**	**0**	**1**	**0**	**0**	**1**	**1**	**1**	**0**	**0**

TABLE 3.3 **Total load buses in the system**

So the bus at same location from array is selected. Now we will try to install capacitors on these load busses. Below shown in Table 3.5 represents a list of the selected candidate buses for shunt capacitor compensation in case where busses are selected randomly.

From research on different sizes of shunt capacitor banks, it was decided to represent the size of the capacitor units as eight different possible sizes of capacitor banks from 0kVAr to 28 MVAR.

Table 3.4 below shows the decimal number which represents the size of capacitor bank to be installed.

Capacitor Bank Size (units)	**Capacitor Bank Size (MVAR)**
0	0
1	4
2	8
3	12
4	16
5	20
6	24
7	28

TABLE 3.4. **Decimal Representation of Capacitor Bank Sizes.**

An example of a chromosome structure is shown below in Figure 3.5. From this example it can be seen that each chromosome consists of 17 decimal numbers. Each number in row **(1)** represents a proposed candidate **bus** on which shunt capacitor is to be placed. The decimal numbers in row **(2),** represent the **size** of the capacitor to be placed at that bus in units.

Chromosome Structure

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	5	3	7	3	2	1	2	3	7	7	1	6	3	7	3	7	3

TABLE *3.5*. Example of a Chromosome Structure.

CREATING THE INITIAL POPULATION

First step to create an initial population of 50 chromosomes, each consists set of 17 genes to represent represents size of capacitors to be placed on the candidate buses. This was accomplished using the following MATLAB function, which forms a 50×17 matrix of random variables between 0 and 7:

Initial = randint(50,17,[0,7])

The second step is to insert each substring i.e. capacitor size of chromosomes in bus data's 11th column which is column of inserted power through capacitors, to calculate total losses with each chromosome.

The third step is to be performed was to run the following MATLAB program called "Load flow" used by [2]. This enabled the total power loss on the system to be calculated for each of the initial chromosomes or for each string of initial population:

```
basemva = 100; accuracy = 0.001; maxiter = 12;
busdata30   linedata30
Lfybus
Lfnewton
Busout
Lineflow
```

The fourth step was to calculate the corresponding fitness value for each of the chromosomes. This was achieved using the fitness function equation given in chapter3.

The fifth step was to find the probability of each fitness function.

The sixth step was to calculate the cumulative sum of probability. It helps us in running the "roulette wheel" selection. This enables the number of times a chromosome is chosen is proportional to its fitness relative to the rest of the population.

The seventh step was to allocate a section of the “roulette wheel” to each of the chromosomes in the population.

Now our main objective is to reduce the system losses so we are considering the minimization problem for our problem.

The following fitness function is often used:

$$F(x) = 1/(1 + f(X))$$

In our problem f(X) is our system losses (real+ reactive losses). (The system losses are calculated with the help of NEWTON RAPHSON load flow technique).

This information does not alter the location of the minimum, but converts a minimization problem to an equivalent maximization problem. The fitness function value of a string is known as the string’s fitness.

(i). Reproduction

Reproduction is the probabilistic process of selecting two parent strings from a population of strings. Here, selection process uses “**ROULETTE WHEEL**” mechanism and the resulting fitness values of the parent strings.

This process is accomplished by calculating the fitness function for each of the chromosome strings in the population and normalizing this set of fitness values to 1. Once these set of values are obtained a simple roulette wheel can be constructed, where each section of the wheel represents a certain string and its relative fitness value. This process ensures that the expected number of times a string is selected is proportional to its fitness relative to the rest of the population. Therefore, strings that have higher fitness values consume a larger portion of the wheel and hence have a higher probability of being chosen to parent offspring and vice versa.

Here during solving problem, we are selecting 50% of parents having highest probability for crossover form total number of population. (So selection rate in our problem is 0.5). This procedure was achieved by introducing two sets of random numbers having size of 13 each, between 0 and 1. 0 as “pick1” and “pick2”, then these random numbers were compared with cumulative sum (CS1) of probability i.e., If $pick1_{(n)} <= CS1_{(n)}$ & $pick1_{(n)} > CS1_{(n-1)}$ then generate parent 1 as (ma) = (n -1). Similar process was done with pick2 to get 13 parents chromosomes as (pa).

This enabled 26 random numbers to be chosen, 13 by pick1 as “ma” and 13 by pick2 as “pa”, with each random number corresponding to a section of the “roulette wheel”.

(ii). Crossover

Crossover is the process of selecting a random position in the string, and swapping the characters either right or left from this position with another similar adjacent string. This random position is called the crossover point. characters to the right of the crossover point are swapped as shown in figure 3.6 (a) and (b).

Parent 1:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	0	1	2	0	1	0	1	1	7	4	7	4	3	7	3	0	1

Parent 2:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	5	3	7	3	2	1	2	3	7	7	1	6	3	7	3	7	3

(a)

Suppose site **6** is selected at random. It means starting from the 7th bit and onwards, bits of strings will be swapped to produce offspring which are given below;

Offspring 1:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	0	1	2	0	1	0	2	3	7	7	1	6	3	7	3	7	3

Offspring 2:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	5	3	7	3	2	1	1	1	7	4	7	4	3	7	3	0	1

(b)

TABLE 3.6 Crossover Operation

(a) Parents, (b) Offspring

(iii). Comparison of Parents and Offspring

Now the new population (offspring) we gets form crossover consists of same number of strings i.e. 50. We checked that which of the population i.e. initial population or offspring from crossover process are best. We calculate power loss with offspring then we calculate fitness function of each chromosome of offspring. Two fitness functions are to be compared with each other and as our requirement is maximum fitness function, because it is inversely proportional to losses of system, the population after crossover should have highest fitness function. If this condition does not satisfy then we have to choose again new random numbers i.e. “pick1” and “pick2” for crossover on initial population to get better results. So fitness function of offspring after crossover, FF2 should be greater than fitness function of initial population, FF1 i.e. ***(FF2 > FF1)***. Else, the process of crossover was continuing with separate random numbers till the best population generated from initial population through crossover.

(iv). Mutation

Mutation is the process of random modification of a string position by changing a “0” to a “1” or vice versa, with a small probability in our case real values are used as population and mutation would be applied on real values by generating random number as shown in Table 3.7. In our case new random numbers are generated between 0.1 to 1 and these random number’s would multiply with selected numbers (selected for mutation randomly) , ceil command is used to get round figure of decimal number as shown in Table below:

3	**7**	**14**	**15**	**16**	**17**	**18**	**19**	***20***	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
0	1	2	0	1	0	1	1	*7*	4	7	4	3	7	3	0	1

Table 3.7. Representation of Mutation

Suppose in row 1, 9th column is selected for mutation, the decimal number over that place would be treated with mutation with mutation operator and its value was changed would change after mutation. In our case, we have used mutrate=0.2.

This process prevents complete loss of genetic material through reproduction and crossover by ensuring that the probability of searching any region in the problem space is never zero. In our problem process of mutation was achieved by choosing a random number between 0.0 and 1.0 for each of the resulting offspring chromosomes. It was decided that mutation would occur on each substring of every string. The chromosomes that the process of mutation was not applied were transferred with no alterations to the chromosomes structure. After crossover now it was turn to apply genetic's next operator i.e mutation. In mutation one bit is change randomly by selecting different random locations.

(v). Convergence Criterion

The iterations (regenerations) of the proposed genetic algorithm are continued until 70% generated chromosomes become equal or the maximum number of iterations is achieved.

3.4 FLOWCHART AND ALGORITHM FOR PROBLEM SOLUTION

In order to simulate the proposed Genetic Algorithm to solve the shunt capacitor placement and sizing problem, a set of steps were produced. These set of steps are shown below, and outline how each of the different sections of a Genetic Algorithm were simulated to produce a solution:

Step 1) Select number of busses for capacitor placement from system:

Generate a set of random numbers to select busses from total load busses in the system, to place capacitors on them.

Step 2) Input System Parameters:

Input system parameters (For example, system topology, and line and load specifications) and the initial population with "initial" chromosomes.

Step 3) Fitness Process:

Step 3A- Run load flow algorithm for chromosome "initial" and save value of total power loss (active/real).

Step 3B- Using total power loss value; compute fitness function (FF) using equation 5.1 for chromosome "initial".

Step 3C- Calculate $FF1=1 / [1+ \text{(system losses)}]$ for each chromosome "initial".

Step4) Reproduction Process:

Step 4A- Set selection rate and number of mating in a pool.

Step 4B- Define total fitness as a sum of values obtained in Step 3C for all chromosomes.

Step 4C- Select a percentage of the "roulette wheel" for each chromosome which is equal to the ratio of its fitness value to the total fitness value.

Step 4D- Calculate cumulative sum (CS1) to normalize the values on the "roulette wheel" between 0.1 and 1.0.

Step 5) Crossover Process:

Step 5A- Choose a pair of random numbers (pick1) and (pick2) between 0.0 and 1.0 to select an individual parent chromosome N_{parent}.

Step 5B - If N_{parent}. ≤ Selection rate (number of chromosomes selected for mating pool) go to Step 5A.

Step 5C- If $pick1_{(n)} <= CS1_{(n)}$ & $pick1_{(n)} > CS1_{(n-1)}$ then generate parent 1 as (ma) =n -1.

Step 5D- Else, transfer the chromosome with no crossover.

Step 5E- Repeat steps 5C to 5D for (pick2) also to generate parent 2 (pa).

Step 5F- Repeat steps 5A to 5D for all chromosomes in a mating pool.

Step 5G- pairing the chromosomes from different location given by ma and pa to generate offspring by applying crossover.

Step 6) Calculate fitness with offspring:

Step 6A- Calculate power loss with new population i.e. offspring.

Step 6B- Calculate fitness function with offspring as FF2=1 / [(1+power losses)].

Step 6C- Compare FF1 with FF2 to check whether offspring are fit enough to give solution or not.

Step 6D- if FF1>FF2 then go to step 5 and repeat complete step till FF1<FF2.

Step 6E- Else, go to step 7.

Step 7) Mutation Process:

Step 7A- Select mutation

Step 7B- Select a random number (rand) for mutation of one chromosome.

Step 7C- Rand is between 0.1 and 1 then apply the mutation process at a random position in the string and go to Step 7D.

Step 7D- Repeat Steps 7A to 7C for all chromosomes.

Step 8) Updating Population:

Replace the old population or (initial) with the new improved population generated i.e. (new initial) by Steps 3 to 6.

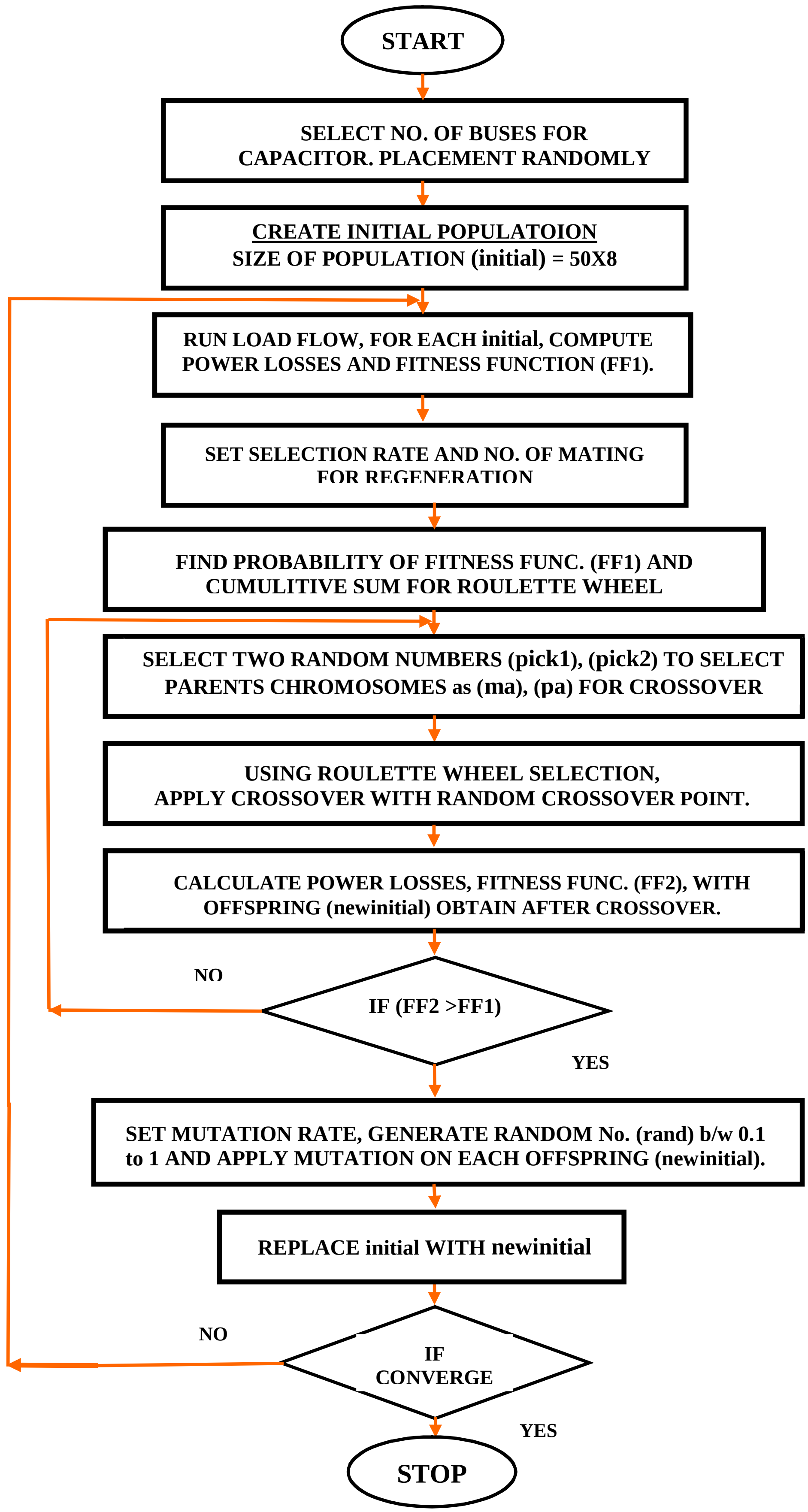
Step 9) Convergence:

If all the fitness values becomes almost constant or the maximum number of iterations have been reached (gen = maxit), then print the solution and stop, else go to Step 2.

FLOWCHART

Figure 3.5 below outlines the structure of the proposed iterative Genetic Algorithm structure for optimal placement and sizing of shunt capacitors, in the form of a flowchart.

FIGURE 3.4 **FLOWCHART of Genetic Algorithm structure for capacitor sizing and placement in optimal power system operation**



CHAPTER 4

RESULTS AND DISCUSSIONS

In this section we have discussed results after the implementation of proposed G.A. method. We use MATLAB code to solve IEEE 30 bus data problem. We are considering two cases for installment of capacitors on its appropriate place. Two cases are:

Case I: All load buses are subjected for compensation

Case II: Maximum six buses are subjected for compensation

In Case I all load buses of system are considered to apply G.A. for capacitor placement. In our case there are 17 total number of load buses in system. And in case II proposed program is selecting six load buses out of 17 for implementation of G.A. Results obtained from genetic algorithm to solve our problem i.e. placement and sizing of capacitor bank in transmission system are shown below, in different tables. The below shown tables consists of initially generated random numbers, *Total injected MVAR* with different *Sizes of shunt capacitors*. In these results we are also showing *Fitness function* of each chromosome and also the effect of injected MVAR on *Voltage* in that particular bus along with losses on the bus.

Our population size of chromosomes was **50x17** in which we are generating *50 chromosomes* with *string length of 17.* These chromosomes are placed along its string length across selected buses. We are calculating fitness for each string of chromosome. R*eal power* and R*eactive power* of the system was also calculated by using Newton Raphon load flow for an every single solution i.e. chromosome. Some of the main required data to run load flow are: base selected for system was 100 MVA, accuracy was 0.001.

The system includes slack bus, generator busses and load busses and our aim was to place capacitor banks on load buses. The capacitors and their capacity to be placed on various load buses are computed using random number as indicated in table 4.1. The integer number indicate the specified capacity as explained in table 4.2.

Load buses	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30
TC=168	0	7	4	1	2	1	6	0	2	1	3	2	5	4	1	0	3

TABLE 4.1. Load busses in system

Capacitor Bank codes (units)	0	1	2	3	4	5	6	7
Capacitor Bank Size (MVAR)	0	4	8	12	16	20	24	28

TABLE 4.2 Assigned codes and there values of capacitor bank size.

CASE I: All load buses are subjected for compensation

In this all 17 load buses are considered capacitor placement and sizing. The initial population generated for these 17 buses are shown in table 4.3. The population represents the size of capacitors in the form of codes and values of these codes are in MVAR which are given as above in table 4.2.

S no.	LOAD BUSES																	FF	PROB	CS
	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30			
1	0	1	2	0	1	0	1	1	7	4	7	4	3	7	3	0	1	**0.0230**	0.0273	0.0273
2	5	3	7	3	2	1	2	3	7	7	1	6	3	7	3	7	3	0.0230	0.0189	0.0462
3	5	2	6	6	6	7	2	6	3	1	0	1	1	7	6	4	3	0.0225	0.0193	0.0656
4	1	4	6	6	2	5	1	3	6	4	1	5	2	6	3	4	7	0.0222	0.0187	0.0843
5	4	3	3	2	3	1	7	5	3	4	3	0	4	6	7	3	1	0.0221	0.0203	0.1046
6	7	7	7	6	5	6	7	7	1	0	0	5	6	3	5	5	1	0.0220	0.0168	0.1214
7	2	2	3	7	2	5	6	0	7	5	0	4	3	1	6	3	0	0.0220	0.0204	0.1418
8	0	5	0	6	5	4	5	6	2	7	1	2	2	1	4	6	6	0.0220	0.0183	0.1601
9	1	7	2	5	7	0	7	0	7	4	7	3	5	2	3	2	4	0.0217	0.0192	0.1793
10	3	2	7	3	7	0	0	2	3	4	4	3	4	6	1	0	3	0.0215	0.0226	0.2019
11	2	2	1	1	6	4	1	5	0	7	2	0	3	0	7	7	2	0.0209	0.0208	0.2227
12	1	5	2	6	7	0	6	0	2	5	6	2	3	0	7	4	5	0.0209	0.0191	0.2418
13	6	7	4	2	0	6	2	7	5	0	6	0	1	1	4	7	1	0.0209	0.0213	0.2631
14	6	0	2	0	6	5	0	3	3	7	6	0	6	0	7	2	0	0.0207	0.0218	0.2849
15	4	7	3	2	1	7	3	5	1	0	2	7	1	3	5	5	1	0.0207	0.0213	0.3062
16	1	5	4	7	7	4	0	5	4	7	4	0	6	4	3	0	6	0.0206	0.0190	0.3252
17	4	7	1	7	3	7	6	0	6	3	3	4	4	1	0	5	1	0.0206	0.0214	0.3466
18	1	3	6	3	4	6	2	0	3	1	5	4	5	3	2	7	5	0.0206	0.0191	0.3657
19	4	0	5	4	1	4	4	2	3	7	1	4	3	4	1	1	5	0.0203	0.0221	0.3877
20	5	1	6	2	3	3	2	7	5	1	6	7	0	6	2	3	2	0.0201	0.0199	0.4077
21	2	4	6	5	5	3	2	7	3	1	3	6	3	5	5	2	6	0.0198	0.0174	0.4251
22	6	5	3	4	7	7	4	5	4	5	6	1	0	5	2	0	5	0.0197	0.0198	0.4449
23	5	2	1	0	1	3	1	4	0	4	0	3	7	3	1	1	0	0.0194	0.0275	0.4723
24	5	6	5	0	7	3	5	5	7	4	0	2	7	4	4	2	6	0.0193	0.0178	0.4901
25	7	2	7	4	5	6	4	7	4	5	3	7	1	1	6	1	0	0.0190	0.0186	0.5087
26	0	1	6	1	3	5	6	0	6	2	0	7	2	0	4	7	3	0.0189	0.0199	0.5286
27	2	7	7	3	1	7	0	3	1	3	4	3	4	1	0	0	6	0.0188	0.0237	0.5523
28	1	7	7	6	7	1	0	1	5	3	2	6	1	2	7	6	7	0.0188	0.0166	0.5689
29	2	1	1	6	5	0	4	4	1	1	4	7	6	3	0	0	5	0.0187	0.0220	0.5909
30	0	7	7	3	5	5	4	7	3	5	6	3	3	2	3	0	3	0.0186	0.0195	0.6104
31	2	0	1	2	6	1	2	5	1	2	3	1	7	0	6	2	5	0.0186	0.0219	0.6323
32	4	5	7	3	5	3	6	3	6	5	2	6	1	6	1	1	2	0.0185	0.0198	0.6521
33	4	4	2	0	0	7	4	2	2	3	2	5	5	2	3	3	5	0.0183	0.0220	0.6740
34	7	0	7	0	2	2	1	2	3	7	4	6	4	7	7	4	2	0.0182	0.0177	0.6917
35	4	7	0	3	0	6	7	1	1	3	3	5	5	7	0	3	2	0.0182	0.0219	0.7136
36	2	1	6	6	0	2	2	1	1	6	0	1	6	7	3	2	2	0.0179	0.0222	0.7757
37	0	2	2	2	6	0	4	1	0	5	2	5	7	1	2	7	1	0.0179	0.0222	0.7580
38	5	2	5	3	0	1	5	3	0	7	0	4	1	2	6	3	6	0.0176	0.0205	0.7785
39	1	1	3	2	5	2	5	7	0	6	6	3	5	4	7	3	1	0.0175	0.0183	0.7968
40	6	7	7	7	6	2	5	1	3	2	5	7	2	7	7	5	5	0.0175	0.0146	0.8115
41	0	2	6	2	5	7	4	3	0	4	3	1	1	6	0	2	7	0.0169	0.0205	0.8319
42	4	6	0	6	0	4	2	1	3	7	7	7	3	4	4	2	6	0.0169	0.0182	0.8502
43	0	0	6	0	7	7	0	3	2	6	7	4	5	5	5	4	6	0.0167	0.0162	0.8664
44	5	0	3	7	0	1	6	6	1	0	1	4	7	3	1	7	3	0.0167	0.0188	0.8890
45	2	1	1	2	3	7	5	0	1	4	0	3	0	4	3	5	2	0.0161	0.0229	0.9081
46	7	7	5	2	7	2	7	0	6	7	5	5	4	7	1	5	0	0.0159	0.0277	0.9258
47	6	1	0	5	4	5	1	7	0	3	1	1	2	4	5	5	7	0.0157	0.0187	0.9445
48	0	4	7	4	2	5	1	2	7	0	7	2	6	3	0	3	7	0.0143	0.0191	0.9637
49	4	6	4	1	3	1	2	7	0	7	4	4	2	3	5	4	6	0.0136	0.0188	0.9824
50	0	6	1	5	3	0	4	4	6	7	5	4	1	3	6	1	3	0.0134	0.0176	1

TABLE 4.3 Initial population

The initial population of table 4.3 represents that the code 0 which has value of 0 MVAR is placed under bus no. 3, code 1 represents that capacitor of 4 MVAR is placed under bus 7. so from this it can be understandable that values of all codes are multiple of 4, such that next bus is 14^{th} bus and 8 MVAR is placed under it, again 0 MVAR is placed under bus 15, 4 MVAR is placed under bus 16. now 0 is placed under bus 17 which shows that there is no compensation provided on this bus i.e. 0 MVAR is placed under bus no. 17. Similarly capacitors are placed under all 17 buses by these random numbers and first row of population is shown in table 4.4. In this way all the codes having population of **50x17** are being treated with the multiple of 4.

L.B	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
SIZE	0	1	2	0	1	0	1	1	7	4	7	4	3	7	3	0	1

TABLE 4.4 First row of initial population

Now its turn to run load flow using initial population for calculating system losses in the form of real and imaginary losses. To run load flow NEWTON RAPHSON has been used and all population i.e. 50x17 chromosomes is being adjusted in bus data's injected MVAR column corresponding to that load bus. Now to check the effect of capacitance in that load bus its losses are considered in terms of real and reactive loss. As our fitness function is **FF= (1/ (1+system losses).** and our requirement is minimum losses in the system, as fitness function is inversely proportional to losses so we require maximum fitness function for our best results.

After calculating fitness function it was turn to apply Genetic operators on initial population i.e. crossover, mutation on initial population. To perform crossover, roullette wheel selection is used for pairing of parents to generate offspring. To apply roullette we calculate probability of fitness function, as

$$P_i = F_i / \sum_{i=1}^{n} F_i$$

Probability of fitness function is shown in figure 4.3. Next step was to calculate cumulative sum of probability, and on the bases of this cumulative sum and generated random number we will find best parents from the initial population to made mating pool for crossover.

Now crossover process is performed by selecting random crossover point as shown below in table 4.5 (a) and (b). Here individual strings are selected at random from the mating pool. Next, a crossover site is selected randomly along the string length and digits (alleles) are swapped (exchanged) between the two strings at the crossover site.

Parent 1:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	0	1	2	0	1	0	1	1	7	4	7	4	3	7	3	0	1

Parent 2:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	5	3	7	3	2	1	2	3	7	7	1	6	3	7	3	7	3

(a)

Suppose site **6** is selected at random. It means starting from the 7th bit and onwards, bits of strings will be swapped to produce offspring which are given below;

Offspring 1:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	0	1	2	0	1	0	2	3	7	7	1	6	3	7	3	7	3

Offspring 2:

Bus	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
Size	5	3	7	3	2	1	1	1	7	4	7	4	3	7	3	0	1

(b)

TABLE 4.5 Crossover Operation

(b) Parents, (b) Offspring

Now fitness function was being calculated with offspring and two fatnesses i.e. fitness with initial population and fitness with offspring was being compared to check whether crossover is providing better results as compared to initial population, we compare two fitness functions of crossover and initial population if crossover provides high fitness as compared to initial then we compute mutation on results of crossover else roulette wheel was applied again for crossover on initial population once again to get better results from initial population. We continued this process of crossover on new parents till we get better results from crossover i.e. high fitness function of crossover results as compared to initial population.

In our case maximum fitness function of initial population was **FF1 = 0.023** and fitness for crossover was **FF2= 0.0274** which means fitness function of crossover is high and this population would give us better results as compared to initial population. System losses are also calculated with each chromosome and their effect on system losses are considered. These losses are shown in table 4.10 in the form of magnitude of real and reactive losses.

After crossover now it was turn to apply genetic's next operator i.e mutation. In mutation one bit is change randomly by selecting different random locations. In our case new random numbers are generated between 0.1 to 1 and these random number's would multiply with selected numbers (selected for mutation randomly) , ceil command is used to get round figure of decimal number as shown in Table 4.6. below

3	**7**	**14**	**15**	**16**	**17**	**18**	**19**	***20***	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**
0	1	2	0	1	0	1	1	*7*	4	7	4	3	7	3	0	1

Table 4.6: Representation of mutation

Suppose in row 1, 9th column is selected for mutation, the decimal number over that place would be treated with mutation with mutation operator and its value was changed would change after mutation. In our case, we have used mutrate=0.2.

Acc. To this result GA is purposing to install **172** capacitance, the result after the completion of first iteration as shown in table 4.7. the result corresponding to the best fitness is indicated in first row.

St no.	Load buses																				FF
	TC	**P**	**Q**	**3**	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**	**FF**
45	172	21.5892	36.4841	2	1	1	2	3	7	5	0	1	4	0	3	0	4	3	5	2	0.0230
9	184	21.5706	36.6055	2	1	7	3	1	7	0	3	1	3	4	3	4	1	0	0	6	0.0230
4	204	22.0622	37.3879	7	0	1	2	3	7	5	0	1	4	0	7	6	3	0	0	5	0.0225
27	208	22.3885	37.8671	2	7	7	3	1	7	0	3	1	3	4	3	4	1	0	0	6	0.0222
10	212	22.2672	38.3178	2	7	1	2	3	7	5	0	1	4	0	7	6	3	0	0	5	0.0221
19	200	22.3002	38.4689	7	0	7	3	1	7	0	3	1	3	4	3	4	1	0	0	7	0.0220
16	188	22.3326	38.4778	7	0	1	2	3	7	5	0	1	4	0	3	0	4	3	5	2	0.0220
2	188	21.9797	38.7137	2	1	2	0	0	7	4	2	2	3	2	5	4	7	1	5	0	0.0220
14	172	22.2306	39.1538	2	1	1	2	3	7	5	0	1	4	0	3	0	4	3	5	2	0.0217
15	192	22.2839	39.6875	2	1	7	0	2	2	1	2	3	7	4	6	0	6	0	2	3	0.0215
37	188	22.9426	40.743	0	2	2	2	6	0	4	1	0	5	2	5	7	1	2	7	1	0.0209
26	200	23.1651	40.6943	7	0	1	6	5	0	4	4	1	1	4	1	1	6	0	2	7	0.0209
36	192	23.0824	40.8108	2	1	6	6	0	2	2	1	1	6	0	1	6	7	3	2	2	0.0209
29	200	23.3237	41.1673	2	1	1	6	5	0	4	4	1	1	4	7	6	3	0	0	4	0.0207
33	212	23.0702	41.3329	4	4	2	0	0	7	4	2	2	3	2	5	5	2	3	3	4	0.0207
22	204	22.9639	41.5392	5	0	0	3	0	6	7	1	1	3	3	5	5	7	0	3	5	0.0206
31	184	23.3063	41.3738	2	0	1	2	6	1	2	5	1	2	3	1	7	0	6	2	5	0.0206
35	228	23.2589	41.4147	4	7	0	3	0	6	7	1	1	3	3	5	5	7	0	3	2	0.0206
6	240	22.9104	42.4934	4	5	6	2	5	7	4	3	0	4	3	1	1	6	0	2	7	0.0203
13	200	23.4456	42.7655	2	1	1	6	5	0	4	4	1	1	4	7	6	3	0	0	4	0.0201
24	244	23.49	43.5112	4	6	6	2	5	7	4	3	0	4	3	1	1	6	0	2	7	0.0198
41	212	23.1773	44.0165	0	2	6	2	5	7	4	3	0	4	3	1	1	6	0	2	7	0.0197
38	212	24.3827	44.1925	5	2	5	3	0	1	5	3	0	7	0	4	1	2	6	3	7	0.0194
3	220	23.7183	45.0481	2	1	7	0	2	2	1	2	3	7	4	4	2	3	5	4	6	0.0193
48	240	23.6122	45.8436	0	4	7	4	2	5	1	2	7	0	7	2	6	3	0	3	7	0.0190
7	276	23.6713	46.1924	4	6	7	3	5	5	4	7	3	5	6	3	3	2	3	0	3	0.0189
32	264	24.2494	46.2779	4	5	7	3	5	3	6	3	6	5	2	6	1	6	1	1	2	0.0188
8	228	24.7421	46.0291	0	7	3	7	0	1	6	6	1	0	1	4	7	3	1	7	3	0.0188
25	220	24.2642	46.6841	2	1	7	0	2	2	1	2	3	7	4	4	2	3	5	4	6	0.0187
49	252	24.2524	46.7128	4	6	4	1	3	1	2	7	0	7	4	4	2	3	5	4	6	0.0186
47	228	24.4014	46.7421	6	1	0	5	4	5	1	7	0	3	1	1	2	4	5	5	7	0.0186
30	264	24.1125	47.131	0	7	7	3	5	5	4	7	3	5	6	3	3	2	3	0	3	0.0185
44	220	25.0883	47.3605	5	0	3	7	0	1	6	6	1	0	1	4	7	3	1	7	3	0.0183
20	244	24.6527	47.8266	2	7	7	0	2	2	1	2	3	7	4	4	2	3	5	4	6	0.0182
21	244	25.4233	47.6989	4	7	3	7	0	1	6	6	1	0	1	4	7	3	1	7	3	0.0182
12	212	25.1347	48.7072	2	1	3	7	0	1	6	6	1	0	1	4	7	3	1	7	3	0.0179
46	308	24.4964	49.2615	7	7	5	2	7	2	7	0	6	7	5	5	4	7	1	5	0	0.0179
42	264	24.8764	49.7964	4	6	0	6	0	4	2	1	3	7	7	7	3	4	4	2	6	0.0176
50	288	24.5871	50.5366	3	4	4	7	6	5	7	3	7	3	6	6	0	6	0	2	3	0.0175
39	244	25.1414	50.2777	1	1	3	2	5	2	5	7	0	6	6	3	5	4	7	3	1	0.0175
1	264	25.9189	52.0289	4	4	5	3	0	1	5	3	0	7	4	6	4	7	7	4	3	0.0169
34	260	25.9573	52.1263	7	0	7	0	2	2	1	2	3	7	4	6	4	7	7	4	2	0.0169
23	244	25.9737	52.9072	0	2	4	1	3	1	2	7	0	7	4	6	4	7	7	4	2	0.0167
5	280	24.9908	53.3868	0	2	7	3	5	6	7	1	1	5	7	7	3	4	4	2	6	0.0167
17	252	26.8008	55.0519	0	2	7	6	7	1	0	1	5	3	2	6	1	2	7	6	3	0.0161
28	276	27.1404	55.4295	1	7	7	6	7	1	0	1	5	3	2	6	1	2	7	6	7	0.0159
43	268	25.6002	57.0332	0	0	6	0	7	7	0	3	2	6	7	4	5	5	5	4	3	0.0157
40	336	28.6887	62.7707	6	7	7	7	6	2	5	1	3	2	5	7	2	7	7	5	4	0.0143
18	344	28.8091	66.2954	1	7	4	7	6	5	7	3	7	3	6	6	4	7	7	4	3	0.0136
11	352	28.9076	67.8533	4	6	4	7	6	5	7	3	7	3	6	6	4	7	7	4	2	0.0134

TABLE 4.7 Results of first iteration

S. no	St no	TC	P	Q	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30	FF
1	45	172	21.5892	36.4841	2	1	1	2	3	7	5	0	1	4	0	3	0	4	3	5	2	0.023

TABLE 4.8 Optimal result of first iteration

The solutions improve as the iteration progresses. After ten iterations FF nearly becomes constant and variations are small. At this the process is terminated and the optimal results are shown in Table 4.9.

Sno.	St.no	TC	P	Q	**Load buses**																	FF
					3	**7**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**29**	**30**	
1	**10**	**60**	**17.4053**	**19.1131**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**0.0372**
2	25	64	17.4254	19.1016	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0.0372
3	27	56	17.4044	19.1494	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	0.0372
4	46	60	17.4205	19.1398	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0.0372
5	17	60	17.4299	19.1779	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	0.0372
6	15	56	17.4065	19.2022	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0.0372
7	4	64	17.4334	19.1914	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0.0371
8	28	64	17.4334	19.1914	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0.0371
9	32	68	17.4528	19.1883	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0371
10	40	68	17.4528	19.1883	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0371
11	9	68	17.4528	19.1883	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0371
12	23	68	17.4528	19.1883	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0371
13	31	60	17.4375	19.2086	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0.0371
14	30	60	17.4379	19.2126	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0.0371
15	20	60	17.4509	19.2020	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0.0371
16	18	60	17.4510	19.2020	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0.0371
17	39	64	17.4469	19.2103	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0.0371
18	49	64	17.4469	19.2103	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0.0371
19	6	56	17.4316	19.2461	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	0.0371
20	5	60	17.4252	19.2549	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0.0371
21	29	56	17.4462	19.2404	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	1	0.0371
22	47	60	17.4293	19.2595	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0.0371
23	50	60	17.4616	19.2408	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	0.0371
24	12	56	17.4424	19.2689	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0.0370
25	35	56	17.4260	19.2845	1	1	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0.0370
26	1	64	17.4584	19.2583	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
27	19	64	17.4584	19.2583	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
28	34	60	17.4408	19.2862	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
29	33	60	17.4418	19.2981	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
30	41	56	17.4466	19.2962	0	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0.0370
31	21	48	17.3904	19.3492	1	0	0	0	1	1	0	1	1	1	1	1	1	1	1	0	1	0.0370
32	42	60	17.4407	19.3069	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
33	2	52	17.4276	19.3241	1	1	0	1	1	1	1	1	0	1	0	1	1	1	1	0	1	0.0370
34	13	60	17.4613	19.2980	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	0.0370
35	22	64	17.4646	19.2965	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
36	11	60	17.4708	19.3133	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0.0370
37	8	60	17.4633	19.3321	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0.0370
38	26	56	17.4672	19.3353	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	0.0370
39	16	52	17.4190	19.4101	1	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	0.0369
40	36	60	17.4857	19.3628	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0.0369
41	48	56	17.4846	19.3800	0	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	0.0369
42	14	48	17.4565	19.4277	0	1	1	1	1	0	1	1	0	1	1	1	1	1	0	0	1	0.0369
43	3	48	17.4565	19.4277	0	1	1	1	1	0	1	1	0	1	1	1	1	1	0	0	1	0.0369
44	43	52	17.4437	19.4395	0	0	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	0.0369
45	45	56	17.4911	19.4183	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	1	1	0.0369
46	38	56	17.4838	19.4262	1	1	1	1	0	1	1	1	0	1	0	1	1	1	1	1	1	0.0369
47	**7**	**44**	**17.4186**	**19.4980**	**1**	**0**	**0**	**0**	**1**	**1**	**0**	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**0**	**1**	**0.0368**
48	37	56	17.4861	19.4415	0	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0.0368
49	44	56	17.4964	19.4519	1	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	0.0368
50	24	56	17.4964	19.4519	1	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	0.0368

TABLE 4.9 Final results for 10^{th} iteration.

The most optimal result with highest fitness function is shown separately in table 4.10. It can be seen that maximum fitness is 0.0372 and corresponding to its 60 MVAR is used to get 17.4053 real power and 19.1131 as reactive power. It suggests to place capacitors on bus no. 3,16,17,19,20,21,23,24,25,26,and 30 i.e. no capacitance on bus 29. If we see the results in table 4.12 the solution with minimum capacitance is on string 7 and is shown separately in table 4.11. Very small difference in fitness function but significant difference in capacitance and the solutions with 44 MVAR capacitance as indicated on string number 7 can be considered if the cost of capacitor is accounted.

S no	TC	P	Q	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30	FF
10	60	17.4053	19.1131	1	1	1	1	1	1	**0**	1	1	1	1	1	1	1	1	**0**	1	0.0372

TABLE 4.10 Optimum results for 10th iteration.

S no	TC	P	Q	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30	FF
7	44	17.4186	19.498	1	**0**	**0**	**0**	1	1	**0**	1	1	1	**0**	1	1	1	1	**0**	1	0.0368

TABLE 4.11 Optimum Result with minimum capacitance.

In this table it was shown that total capacitance used is 11 capacitors of 44 MVAR and real losses are 17.4186 and reactive losses are 19.1131 which was almost same as compared to losses by installing 16 capacitors of 60 MVAR. The price of each capacitor is also high so to make the system economical we can consider the result of table 4.11 as our optimal solution to place minimum capacitance. We use 10 iterations to obtain this result and at 10^{th} iteration, fitness function has become almost constant. It has difference of **0.0001,** so our accuracy is **0.0001.**

Bus no.	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30
V	1.0394	1.0175	1.1118	1.1059	1.1042	1.0902	1.0997	1.0942	1.0939	1.0814	1.0826	1.0946	1.0774	1.0832	1.0666	1.0859	1.0775

TABLE 4.12 Change in Voltages after optimization

Correspondingly the load flow solution indicates the change in bus voltage profile is indicated in Table 4.12. According to results it is presented the change in voltage in pre compensated and post compensated stages is approximately 8 percent.

Now the comparison of system after proposed GA and before optimization is shown in table 4.13 which shows our optimization reduce real losses , reactive losses and improves average voltage of system.

Parameters	Before optimization	After proposed G.A optimization
Capacitor Bank Locations and Size (MVAR)	No Compensation	Bus no.3=4(MVAR) Bus no.7=0(MVAR) Bus no.14=0(MVAR) Bus no.15=0(MVAR) Bus no 16=4(MVAR) Bus no.17=4(MVAR) Bus no.18=0(MVAR) Bus no.19=4(MVAR) Bus no 20=4(MVAR) Bus no.21=4(MVAR) Bus no.22=0(MVAR) Bus no.23=4(MVAR) Bus no.24=4(MVAR) Bus no.25=4(MVAR) Bus no.26=4(MVAR) Bus no.29=0(MVAR) Bus no.30=4(MVAR)
Total Capacitance	0 MVAR	44 MVAR
Real losses (P)	17.594 MW	17.4186 MW
Reactive losses(Q)	22.233 MVAR	19.1131 MVAR
Total losses(P+jQ)	17.594+j22.233	17.4186+j19.1131
Average Voltage	1 Volt	1.0827 Volt
Accuracy		0.0001

TABLE 4.13 Comparison after optimization

The solution given by this method can also be represented diagrammatically as shown in figure 4.1

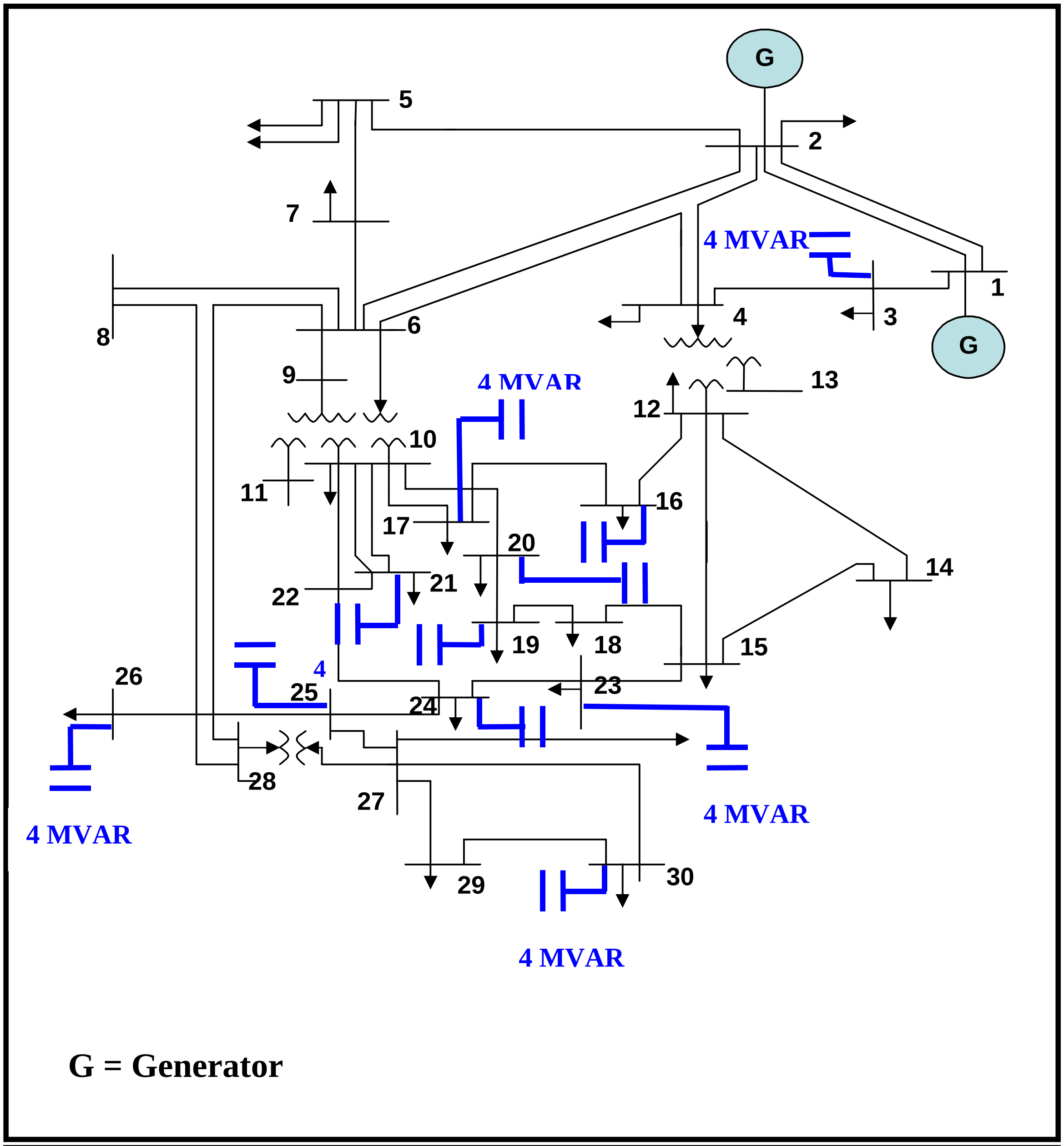


Figure 4.1 Diagrammatically representation of results

CASE II: Max six buses are subjected for compensation

The installation of capacitors on large number of load buses is not economical and therefore it is to place capacitor on specified number of randomly selected buses rather than to place capacitors on all system load buses. Therefore the capacitor placement for maximum six out of seventeen load buses is considered. The buses are selected randomly

In this case load flow calculate system loses only by considering the capacitance on selected load buses, for rest of load busses load flow considered 0 MVAR as injected power. In this case the proposed GA's algorithm was same as we use for CASE I but the only difference was that, load buses for capacitor placement is selected in the first step of algorithm before initialization of population. The next steps were same as done in CASE I. load flow was run for selected bus on that bases fitness function with initial was being calculated, next step was to apply roullette wheel and then crossover. Then fitness with offspring was compared with initial fitness function to check whether new generated offspring are useful to give solution. The solution after first iteration is shown below in table 4.13.in this table maximum suggested MVAR is 76.

Sno.	LOAD BUSES																				FF
	TC	P	Q	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30	
1	76	17.472	19.360	6	0	0	0	0	0	0	0	5	0	5	0	0	0	1	0	2	0.036930
2	60	17.484	19.493	2	0	0	0	1	0	0	0	4	0	5	0	0	0	2	0	1	0.036785
3	76	17.729	19.592	5	0	0	0	5	0	0	0	2	0	6	0	0	0	1	0	0	0.036466
4	48	17.552	19.917	4	0	0	0	2	0	0	0	3	0	3	0	0	0	0	0	0	0.036302
5	60	17.806	20.016	4	0	0	0	5	0	0	0	3	0	3	0	0	0	0	0	0	0.035984
6	60	17.806	20.016	4	0	0	0	5	0	0	0	3	0	3	0	0	0	0	0	0	0.035984
7	88	17.99	20.231	4	0	0	0	5	0	0	0	5	0	3	0	0	0	3	0	2	0.035621
8	92	17.948	20.298	5	0	0	0	4	0	0	0	6	0	3	0	0	0	1	0	4	0.035593
9	88	17.969	20.343	3	0	0	0	5	0	0	0	4	0	5	0	0	0	1	0	4	0.035533
10	76	18.008	20.437	2	0	0	0	3	0	0	0	3	0	6	0	0	0	4	0	1	0.035412
11	56	18.103	20.776	2	0	0	0	5	0	0	0	2	0	0	0	0	0	2	0	3	0.035018
12	88	18.036	20.990	5	0	0	0	0	0	0	0	5	0	6	0	0	0	1	0	5	0.034874
13	104	18.277	20.800	6	0	0	0	6	0	0	0	4	0	5	0	0	0	1	0	4	0.034857
14	72	18.392	21.162	3	0	0	0	3	0	0	0	0	0	6	0	0	0	5	0	1	0.034439
15	64	18.351	21.219	2	0	0	0	2	0	0	0	0	0	6	0	0	0	5	0	1	0.034419
16	92	18.226	21.354	2	0	0	0	5	0	0	0	5	0	5	0	0	0	1	0	5	0.034395
17	64	18.732	21.711	5	0	0	0	6	0	0	0	0	0	0	0	0	0	4	0	1	0.033698
18	100	18.631	22.088	6	0	0	0	3	0	0	0	3	0	4	0	0	0	4	0	5	0.033449
19	76	18.576	22.221	5	0	0	0	0	0	0	0	5	0	3	0	0	0	0	0	6	0.033375
20	96	18.825	22.172	4	0	0	0	4	0	0	0	4	0	6	0	0	0	5	0	1	0.033238
21	80	18.737	22.384	4	0	0	0	2	0	0	0	0	0	5	0	0	0	5	0	4	0.033122
22	88	18.795	22.362	5	0	0	0	3	0	0	0	0	0	5	0	0	0	5	0	4	0.033100
23	88	18.788	22.378	5	0	0	0	3	0	0	0	0	0	5	0	0	0	5	0	4	0.033091
24	88	18.683	22.478	3	0	0	0	4	0	0	0	3	0	5	0	0	0	1	0	6	0.033081
25	76	18.726	22.496	5	0	0	0	0	0	0	0	0	0	5	0	0	0	5	0	4	0.033036
26	80	18.788	22.465	3	0	0	0	3	0	0	0	0	0	5	0	0	0	5	0	4	0.033019
27	88	18.688	22.737	5	0	0	0	1	0	0	0	2	0	6	0	0	0	2	0	6	0.032860
28	56	18.718	22.861	5	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	6	0.032737
29	92	18.961	22.670	4	0	0	0	5	0	0	0	0	0	5	0	0	0	5	0	4	0.032729
30	104	19.052	22.624	5	0	0	0	5	0	0	0	4	0	6	0	0	0	5	0	1	0.032703
31	88	18.962	22.716	3	0	0	0	5	0	0	0	0	0	5	0	0	0	5	0	4	0.032690
32	68	18.982	22.876	4	0	0	0	5	0	0	0	0	0	2	0	0	0	0	0	6	0.032547
33	76	19.183	22.736	4	0	0	0	2	0	0	0	4	0	2	0	0	0	6	0	1	0.032523
34	64	18.986	22.939	3	0	0	0	5	0	0	0	0	0	2	0	0	0	0	0	6	0.032491
35	64	18.811	23.125	5	0	0	0	0	0	0	0	2	0	1	0	0	0	2	0	6	0.032457
36	72	19.168	22.847	5	0	0	0	0	0	0	0	4	0	2	0	0	0	6	0	1	0.032444
37	100	18.915	23.116	4	0	0	0	5	0	0	0	2	0	6	0	0	0	2	0	6	0.032395
38	96	18.914	23.155	3	0	0	0	5	0	0	0	2	0	6	0	0	0	2	0	6	0.032364
39	112	19.228	22.974	6	0	0	0	6	0	0	0	4	0	6	0	0	0	5	0	1	0.032301
40	96	19.001	23.167	5	0	0	0	3	0	0	0	6	0	1	0	0	0	4	0	5	0.032297
41	88	19.226	23.154	5	0	0	0	0	0	0	0	5	0	4	0	0	0	6	0	2	0.032159
42	76	19.367	23.038	4	0	0	0	4	0	0	0	0	0	4	0	0	0	6	0	1	0.032158
43	88	19.411	23.020	4	0	0	0	5	0	0	0	4	0	2	0	0	0	6	0	1	0.032142
44	80	19.005	23.392	1	0	0	0	3	0	0	0	6	0	1	0	0	0	4	0	5	0.032114
45	84	18.989	23.451	5	0	0	0	0	0	0	0	6	0	1	0	0	0	3	0	6	0.032077
46	80	19.47	23.174	4	0	0	0	5	0	0	0	0	0	4	0	0	0	6	0	1	0.031982
47	80	19.466	24.085	4	0	0	0	2	0	0	0	4	0	0	0	0	0	5	0	5	0.031282
48	72	19.479	24.218	2	0	0	0	2	0	0	0	4	0	0	0	0	0	5	0	5	0.031172
49	104	19.627	24.879	5	0	0	0	3	0	0	0	5	0	2	0	0	0	5	0	6	0.030591
50	120	20.088	25.773	6	0	0	0	6	0	0	0	5	0	2	0	0	0	5	0	6	0.029694

TABLE 4.13 Results with first iteration

To get better results iterations have to run and after 10 iterations results are obtained as shown in table 4.14.In this table it can be seen that out of 17 buses there are 6 buses selected randomly. These buses are 3, 16, 20, 22, 26, 30 and solution to place capacitor of particular size is placed under them as shown in table. 4.14. The total fitness is also calculated for every solution as shown in last column of table 4.14. This system provides us solution by placing 4 capacitors of 4 MVAR each on every selected bus. The real loss is 17.511 MW and reactive loss is 19.056 MVAR. the most optimal solution is shown in first row in bold letters. It has highest fitness of 0.037203.

S.no	LOAD BUSES																				FF
	TC	P	Q	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30	
1	16	17.511	19.056	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0.037203
2	16	17.511	19.25	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0.037005
3	16	17.491	19.276	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0.036997
4	20	17.693	19.115	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.036974
5	24	17.674	19.183	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.036922
6	16	17.672	19.227	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0.036880
7	24	17.670	19.304	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.036805
8	24	17.670	19.304	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.036805
9	24	17.670	19.304	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.036805
10	16	17.542	19.458	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0.036767
11	16	17.536	19.687	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0.036543
12	20	17.733	19.631	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0.036425
13	16	17.622	19.911	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0.036246
14	20	17.754	19.794	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0.036246
15	24	17.944	19.803	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.036071
16	16	17.656	20.136	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0.035996
17	20	18.153	20.275	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0.035443
18	20	18.213	20.355	1	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0.035319
19	16	18.164	20.723	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.035018
20	16	18.244	20.758	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0.034921
21	20	18.285	20.892	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.034766
22	20	18.293	20.965	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.034693
23	20	18.299	20.973	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.034682
24	20	18.324	20.972	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0.034662
25	20	18.324	20.972	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0.034662
26	16	18.269	21.077	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0.034610
27	20	18.317	21.132	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0.034524
28	16	18.308	21.205	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0.034465
29	20	18.398	21.164	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.034432
30	20	18.595	21.509	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.033976
31	24	18.678	21.677	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.033768
32	20	18.611	21.788	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0.033721
33	20	18.769	21.779	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.033613
34	20	18.762	21.884	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.033528
35	20	18.782	22.046	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.033375
36	20	18.942	22.356	1	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0.033001
37	20	18.936	22.562	1	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0.032836
38	20	19.020	22.545	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.032791
39	20	19.019	22.769	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.032608
40	24	19.182	23.094	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.032236
41	24	19.172	23.222	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.032140
42	16	19.406	23.269	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0.031949
43	16	19.417	23.264	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0.031946
44	16	19.400	23.292	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0.031936
45	24	19.592	23.883	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.031357
46	20	19.369	24.221	0	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.031237
47	16	19.626	24.132	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.031148
48	20	19.798	24.741	1	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0.030593
49	24	20.133	25.874	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.029600
50	24	20.158	25.884	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0.029580

TABLE 4.14 Results for CASE II.

The effect of capacitance on voltage was also calculated and is shown in table 4.15. It was seen that there was slight change in voltage profile of busses by installing capacitor banks in system as shown in table its changing from unity to some fractions.

Bus No.	3	7	14	15	16	17	18	19	20	21	22	23	24	25	26	29	30
V	1.031	1.016	1.086	1.077	1.085	1.080	1.063	1.057	1.060	1.063	1.065	1.065	1.059	1.075	1.1306	1.1058	1.0316

TABLE 4.15 Change in voltage in CASE II

Parameters	Before optimization	After proposed G.A optimization
Capacitor Bank Locations and Size (MVAR)	No Compensation	Bus no.3=4(MVAR) Bus no.7=0(MVAR) Bus no.14=0(MVAR) Bus no.15=0(MVAR) Bus no.16=4(MVAR) Bus no.17=0(MVAR) Bus no.18=0(MVAR) Bus no.19=0(MVAR) Bus no.20=0(MVAR) Bus no.21=0(MVAR) Bus no.22=4(MVAR) Bus no.23=0(MVAR) Bus no.24=0(MVAR) Bus no.25=0(MVAR) Bus no.26=4(MVAR) Bus no.29=0(MVAR) Bus no.30=0(MVAR)
Total Capacitance	0 MVAR	16 MVAR
Real losses (P)	17.594 MW	17.511 MW
Reactive losses (Q)	22.233 MVAR	19.056 MVAR
Total losses (P+jQ)	17.594+j22.233	17.511 +j19.056
Average Voltage	1 Volt	1.06764 Volt
Accuracy		0.0001

TABLE 4.16 Comparison after optimization CASE II

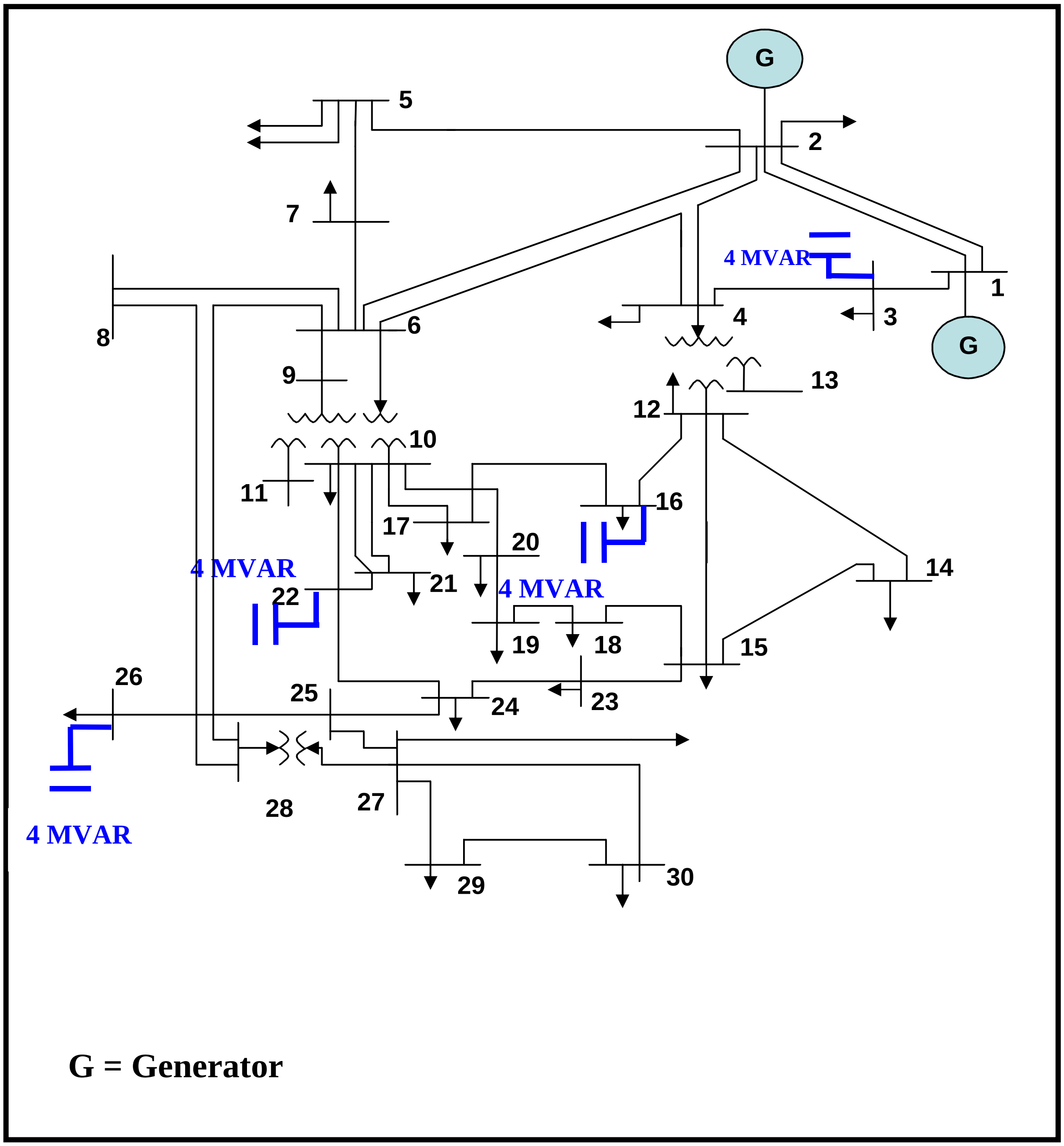


FIGURE 4.2 Representation of solution in line diagram.

In this diagram the capacitors are shown with their size on its appropriate location.

CHAPTER-5

CONCLUSION AND FUTURE SCOPE

CONCLUSIONS

The importance of sizing and placement of shunt capacitors at various load buses for loss minimization has been identified. The same problem has been attempted using GA. In this two cases are considered namely:

Case-I, in this case all load buses are considered simultaneously for reactive compensation and in Case-II, maximum six load buses are considered for reactive compensation. The reactive losses before compensation was 22.233 MVAR and in case-I, it becomes 19.1131 MVAR and in Case-II, it comes out to be 19.056 MVAR. The objective to reduce the losses has been achieved in both the cases. However, as expected, higher fitness is achieved in Case-I because all the buses are considered for reactive compensation. However, it needs higher investments.

Case-II. Only 4 MVAR capacitance at Four location bus number are selected at bus number 3, 16, 26, 30, which is more economical as compared to Case I where we select all load buses for capacitor placement. The real losses in Case II is **17.511 MVAR** and reactive losses are **19.056 MVAR.** So from results it is clear that reactive power in our system is decreasing as compared to pre compensated state. Voltage profile is also improving by applying this proposed GA method.

FUTURE SCOPE

1. The method can be extended to include other compensation particularly including FACTS or STATCOM.
2. Optimize the results while having overall economics consideration in objective function by including factors like the cost of compensation, net saving due to reduction in losses, quality restriction in objective.

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