2010-01-01

Component Replacement Analysis For Electricity Distribution Systems Using Evolutionary Algorithms

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COMPONENT REPLACEMENT ANALYSIS FOR ELECTRICITY DISTRIBUTION

SYSTEMS USING EVOLUTIONARY ALGORITHMS

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Dedicated

To my late father, my mother and my sisters

For all their sacrifices, support and unconditional love throughout my life

COMPONENT REPLACEMENT ANALYSIS FOR ELECTRICITY DISTRIBUTION SYSTEMS USING EVOLUTIONARY ALGORITHMS

by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

Department of Industrial, Manufacturing and Systems Engineering

THE UNIVERSITY OF TEXAS AT EL PASO

December 2010

ACKNOWLEDGEMENTS

It is a very difficult task to dedicate one or two pages to mention and thank all those wonderful people who helped me during my journey that stretched over two and a half years of exciting work here at (UTEP) The University of Texas at El Paso.

At the forefront of those whose support and mentorship presented the major driving force to bring this work into completion, comes from my thesis advisor and my mentor Dr. Jose F. Espiritu. I am extremely grateful to Dr. Espiritu, whose encouragement, guidance and support from the initial to the final stage of my thesis enabled me to develop an understanding of the subject. Without his guidance and persistent help this thesis would not have been possible.

I would like to acknowledge the invaluable guidance, concern and support of Dr. Heidi Taboada. Your words and your feedback have always encouraged me to excel in my academic life. Thank you so much.

I am grateful to my mother and thankful to my 4 sisters for their patience, understanding, continuous support, encouragement and unconditional love.

My special thanks to my brother-in-law V. Sridhar and my sister V. Suvarna for their financial support throughout my professional education and always believing in me. You are my role model and I would have never achieved my academic goals had it not been for your support, love and encouragement.

Last, but not the least, I would like to dedicate this thesis to the spirit of my deceased father who always inspired me to be a better person. His words are always in my mind.

ABSTRACT

The main objective of the electric power grid is to supply economical and reliable electricity to industrial, commercial, household, transportation, and other end-users, including agricultural, educational institutions and hospitals. The power system is a very large and complex network consisting of generation, transmission, and distribution systems. The main focus of the present research is in the area of power distribution systems. Almost all the areas of the power grid uses simpler radial distribution systems to distribute electricity to the end consumer, it is the final and therefore vital link between the consumer and the rest of the power grid. Therefore it is very important to have a very robust, economical and reliable power distribution system.

In this research, a new model is developed to determine optimal replacement policy for the components involved in power distribution system. The model considers two different types of potential decisions to be made at the beginning of each planning period, either to keep the component in the system for one more planning period or to replace it with a new component. The main objective of this algorithm is to obtain an optimal replacement schedule over a finite time horizon subject to annual budget constraints. Genetic algorithm is used to solve this model and is applied to two different radial configurations which are commonly used by the power industries.

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Chapter 1

INTRODUCTION

1.1 Research Background:

A strong and persistent rise in the importance of electricity is one of the major long-term trends in the history of energy, prevailing in human development since centuries. In a remarkable profusion of applications, electricity has penetrated deeply and brought important changes into virtually every area of human life, whether in industries, in hospitals, in the home, or in the various rapidly growing commercial and service sectors. Therefore, electricity is undoubtedly most integral part of human development in the various sectors and absence of electricity not only causes inconvenience, but also economic losses due to reduced commercial and industrial production. Hence the primary objective of an electric power system is to provide electricity to the customers and satisfy the required needs as economically and reliably as possible with a reasonable assurance of continuity and quality.

The power grid basically consists of three distinct divisions namely, the generating station, transmission network, and distribution network. The focus of the present research is in the area of electricity distribution system. The distribution system is an important part of the total electrical supply system, as it provides the final link between a utility's bulk transmission system and its customers. The distribution system is generally considered to begin at the substation and end at the customer's meter. It has been reported that 80% of all customer interruptions occur due to failures in the distribution systems. Therefore, it is very important to have very robust and reliable electricity distribution systems in order to cater to the ever increasing demand of electricity from the consumer market.

Component replacement analysis consists of determining the correct time or schedules to replace certain components in the system such that some total cost function is minimized. Given a level of output or service expected from a component over a period of time since its installation in the system, a decision is required to be made periodically to either keep that component for one more planning period, replace that component with a new component, or to do some sort of maintenance on the existing component, as it wears out with the aging process. In general the component replacement problem can be categorized as either serial or parallel replacement problem. Serial replacement problem considers a single component or multiple independent components to be replaced at a given point of time and it is assumed that there is no economic interdependencies exist among the components that provide the service together. On the other hand, a parallel replacement problem considers components that are economically interdependent and operate in parallel. And with the inclusion of the constraints in this type of replacement problems, the desired solutions which includes keep and replace decisions for each component over the planning period, results in a complex combinatorial optimization problem for component replacement.

The field of metaheuristics for the application to combinatorial optimization problems is a rapidly growing field of research. This is due to the importance of combinatorial optimization problems for the scientific as well as the industrial world. Many optimization problems of practical as well as theoretical importance consist of the search for a "best" configuration of a set of variables to achieve some goals. The goal of combinatorial optimization is to find a discrete mathematical object that maximizes (or minimizes) an arbitrary function specified by the user. In the present research Genetic Algorithms are used to solve the component replacement problems in power distribution systems.

Genetic algorithms (GA's) are optimization methods inspired by evolutionary adaptation in nature. They were introduced by Holland in the early 1970s and implemented for optimization problems by Goldberg in the late 1980s. In terms of searching behavior, simple GA's fall into the category of global optimization methods, as trial solutions of a GA run are generated based on global information accrued throughout the search process. The optimization mechanism of GA's can be briefly described as follows:

- GA's operates on a population of chromosomes, each representing a trial solution to the problem being solved.
- The fitness of a chromosome, which is normally defined to correspond to the criterion of the optimization problem being solved, is evaluated.
- In each iteration or generation, relatively fit chromosomes are selected to undergo a series of genetic operations to produce a population of offspring.
- In this way, better chromosomes (trial solutions) are evolved throughout the optimization process, and the fittest chromosomes found during a GA run are regarded as the optimized solution.

Literature is in abundance when it comes to successful application of GA's in finding the solution for a wide variety of optimization problems. However, GA's are unconstrained search techniques. Thus, incorporating constraints into the fitness function of GA is an open research area. There are various methods of handling these constraints and most work has been done in the past by incorporating penalty functions with GA's to solve these complex constraint problems.

The basic idea of penalty functions is to transform a constrained optimization problem into an unconstrained optimization problem by simply adding (or subtracting) a certain value to or from the objective function based on the amount of constraint violation present in a certain solution. Penalty functions replace constrained optimization with a series of less constrained conditions whose solutions ideally converge to the solution of the original constrained problem. The penalty function itself grows and forces the merit function to increase in value when the constraints are violated, and causes no growth when constraints are not violated. In the present research method death penalty functions are used to penalize the infeasible solutions.

Like many other combinatorial problems found in the field of power systems optimization, the component replacement problem presents a multimodal aspect. This is a hard, large scale combinatorial problem in which the number of local minimum solution points and the number of options in the form of different schedules obtained, to be analyzed increases exponentially with the size of the distribution system.

Determination of the optimal component replacement schedules is not an easy task to handle. The complexity lies in the high degree of interaction between various components involved at various levels of the power distribution network. Also variables existing from the number of uncertainties existing in the system, including the supply demand ratio, forced outage of generating units and the environmental issues accompanying the system. Consequently, the number of component replacement schedules is generally large, thus requiring a systematic approach in order to ensure that optimal or near optimal replacement policies are selected subject to problem constraints.

1.2 Research Objectives:

In the present research work, a Genetic Algorithm is developed to obtain component replacement model for power distribution system over the finite planning horizon; the model developed is applied to a Radial Configuration which is most commonly used configuration in power industry. The main objective of this research is to minimize the total cost of the replacement of the components involved in the power distribution system, subject to budget constraints.

In order to meet the goal, several other objectives are addressed such as to develop a generalized formulation for the component replacement policies pertaining to power systems problems in which various issues such as objectives and constraints commonly encountered in the real-world power distribution systems are examined. This is followed by developing a framework for utilizing Genetic Algorithms to determine optimal component replacement schedules for power systems, using appropriate penalizing formulation for the solutions that are infeasible. And lastly to test the developed dynamic GA model on two different radial configurations, that's presented in the later section of the thesis.

1.3 Thesis Layout:

The thesis is organized as follows:

Chapter 2 presents a brief description of the main topic, what is component replacement analysis. This is followed by categorizing the different types of replacement methods available such as serial replacement and parallel replacement. These methods are explained in brief and later in the chapter a thorough literature review is presented demonstrating the application of component replacement analysis in various engineering fields, done by the researchers in the past.

Chapter 3 presents the basic concepts of electricity generation, transmission, and distribution systems. Various stages of the electricity generation, transmission and distribution

network are explained in detail. Since the present area of research is concerned with the power distribution systems, more emphasis is placed on understanding the working, critical factors involved, various components involved and the importance of the distribution network.

A metaheuristic is general solution method that provides both a general structure and strategic guidelines for developing a specific heuristic method to fit a particular kind of optimization problem. Several algorithms that can be used to obtain optimal solution for various combinatorial optimization problems include exact methods such as Linear Programming, Integer Programming models etc., and metaheuristic approaches such as Tabu Search, Simulated Annealing and Ant Colony Optimization to name a few.

These exact optimization methods and metaheuristics approaches are presented in Chapter 4. First section presents the brief explanation and understanding of combinatorial optimization problems followed by brief description of various exact optimization methods like Linear Programming, Integer Programming, and Dynamic Programming. Later sections provides an elementary introduction to metaheuristics describing the general nature of metaheuristics followed by illustration of metaheuristic approaches such as Tabu Search and evolutionary algorithms such as Ant Colony Optimization, Particle Swarm Optimization and Genetic Algorithms. Considering the application of Genetic Algorithms in this present research area, this algorithm is explained in detail in the later sections of the chapter.

Constrained optimization is a very important aspect when it comes to solving the combinatorial optimization problems. In the present research the objective function is subject to annual budget constraints. Therefore constraint handling techniques are presented in the Chapter 5. Although there are several approaches proposed in GAs to handle constraint optimization problems, the most popular approach in GA community to handle constraints is to use penalty

functions that penalize infeasible solutions by reducing their fitness values in proportion to their degrees of constraint violation. This chapter provides an in-depth knowledge of the penalty function methods from the point of view of its application using evolutionary algorithms. Based on this information, Static, Dynamic, Adaptive and Death Penalty functions are presented followed by the literature review of the applications of each of these above mentioned penalty function methods in the constraint optimization problems.

Chapter 6 presents the methodology, formulation and the model developed in this present research. Firstly, a detail literature review is presented regarding the application of various metaheuristic approaches in obtaining optimal solutions for the various optimization problem domains. This section also presents the application of GAs in various component replacement problems investigated by various researchers in the area of power systems. Later, Non-Homogenous Poisson Process (N.H.P.P) method is presented which is used to calculate the aging process of the components involved in the power systems. Various formulations used to calculate the total cost of the component replacement schedules, which includes maintenance cost, unavailability cost and purchase cost of the component under consideration is presented which eventually guides us to derive the main objective function of the present research. Later sections of the chapter presents the algorithm developed, along with the detailed explanation of the various steps involved in obtaining the optimal solution for component replacement problem. This developed GA model is tested on examples using two radial configuration systems with the finite planning periods. This is followed by the results obtained, the solution representation and finally the conclusions and the future scope of work in this research area.

Chapter 2

COMPONENT REPLACEMENT ANALYSIS

2.1 What is Replacement Analysis?

Replacement analysis is a useful tool offering individuals and organizations the techniques to model economic decision making problems, such as maintenance and replacement decisions, and determine an optimal decision. Component replacement analysis can be viewed as a configuration selection problem which assesses „if and when' a certain piece or pieces of a component or equipment should be installed in a given configuration to keep the whole system in efficient working conditions. Determining the optimal procedure of replacement of old machines or assets by new ones is the problem of continuing interest in the field of industrial economics, operations research, and management sciences. Many types of assets that provide a service or produce a product are replaced over time. Some examples include machines, tooling, buildings, roads, and bridges. Replacement of an asset or a component is inevitable when an asset fails completely and cannot be repaired, or when the cost of keeping an asset in operation is prohibitive, or when changes in technology make an asset inferior, outdated or obsolete, or simply when a change is desired. From a monetary perspective, the objective of an asset replacement analysis is to provide the required service over some predetermined planning horizon in the most economical and efficient manner.

In general the component replacement analysis involves the decision of whether or not to replace an existing asset with a new asset. Component replacement analysis is concerned with determining the optimal (1) time to remove a current asset (defender) from service and (2) selection of another asset (challenger) to take its place. The performance of components within

most operating systems deteriorates with the growing age thus making the equipment more expensive to be kept operational in the system hence component replacement analysis is designed to minimize operating costs by identifying the optimal time periods to replace aging components with new or refurbished replacement equipment. As these components are utilized over time, they grow old with time, become worn and lead to increased operating and maintenance expenditures. Therefore, the timely replacement of these assets is necessary to assure economically efficient operations.

Determining minimum cost replacement schedules requires the analysis of current and future costs over some time horizon. Given a level of output or service required from an asset over time, a decision is made periodically, to either keep or replace the asset, as it wears with the aging process. This sequence of keep and replace decisions over the given time horizon is determined, such that some total cost function is minimized. Different types of costs include capital or replacement costs (purchase costs and salvage revenues), operating and maintenance costs, and cost of unmet demand (referred to as opportunity costs). In general, a replacement problem can be categorized as either serial or parallel replacement.

2.2 Types of Replacements:

Replacement problems involves determining an optimal replacement schedule that results in a minimum total cost of owning and operating an asset or a fleet of assets over a finite or infinite planning horizon. There are two types of replacement methods: Serial Replacement and Parallel Replacement.

2.2.1 Serial Replacement:

Serial replacement problems consider a single asset or multiple independent assets. In serial replacement problems, it is assumed that a single component replaces another single component, or a set of components replaces another set and the components that provide the service collectively in the network or a system have no economic interdependence. Therefore, their replacement decisions can be made separately. The serial replacement problem, which analyzes the replacement of a single asset or multiple independent assets, is well studied in the literature. In the single asset case, a deterministic utilization pattern is generally assumed and decisions are made periodically, based on the age of the asset. In series replacement analysis, the assets operate in series, and thus, demand is served by the group of assets which operate in sequence. An example of this situation would be a production line in which multiple machines must operate together to meet a demand or service constraint. Generally, the capacity of the system is defined by the smallest capacity asset in the line. And also the situations exist with assets both in series and parallel with capacity definitions following suit.

2.2.2 Parallel Replacement:

Many real world equipment replacement problems involve selecting two or more types of machines from a set of one or more types of possibilities. These possible alternative machines may have different capacities and costs of purchase and operational costs associated with them. Often the capacities of the machines may be such that more than one machine is necessary to satisfy production requirements. Thus the problems in which more than one machine may operate at a given time are referred to as parallel replacement problems. There are two major difficulties in analyzing the replacement problem whereby the components under consideration are part of a large integrated system: the interactive nature of an integrated system and the

combinatorial nature of replacement alternatives. The models may be categorized as either parallel replacement problems, or series replacement problems. In both of these problems, the assets are economically interdependent in that they are subject to demand and/or budgeting constraints and/or have costs that are not linear with respect to the number of assets, such as economies of scale in purchase price. However, in parallel replacement models, it is assumed that the assets operate in parallel and thus contribute to demand independently. From the real application standpoint, parallel replacement problems occur widely in many situations. Examples are government agencies or private business organizations that maintain fleets of vehicles and equipment to satisfy public service demands (e.g., transportation or performing specific tasks). Vehicles in such fleet can be organized into classes, where a class may be categorized by size and/or function. Within a class, vehicles are usually varied in their ages and cumulative mileages. This variety directly effects on preferences shown by the users in that they more often select newer vehicles. In other words, usage pattern in some actual situations can be stated as follow: given various vehicles available to provide the same service or function, it is the newer ones that are generally preferred. When replacements decisions are made, the effect of this usage pattern should be considered. That is because as older vehicles are replaced by new vehicles, the new vehicles become the most highly utilized, which in turn affects their cumulative mileages and operational costs. Another example would be a fleet of trucks that service a distribution center. The total capacity available is the sum of the individual capacities of the trucks

Parallel replacement problem considers assets that are economically interdependent and operate in parallel and it involves a trade-off between the capital expenses of acquiring new assets, capital gains from salvage values of old assets, and the operational costs of new versus old assets. Economic interdependence may result from system-level budget constraints, demand

constraints or service requirements. For parallel replacement problems, the desired solutions includes keep and replace decisions for each individual asset over the planning horizon, resulting in a difficult combinatorial optimization problem as the replacement of groups of assets must be analyzed.

2.3 Applications:

One of the most practical and interesting areas of engineering economics is replacement analysis considering the fact that almost all the businesses and manufacturing firms frequently have to decide which of their existing equipment to replace, taking into account future changes in capacity requirements. Demand for new plant and equipment arises primarily from two sources: replacement of existing equipment, and additional equipment required for meeting the growth expected in demand for the firm's products and services. The replacement of equipment, in turn, is induced by the physical deterioration of older equipment with age, resulting in higher operating and maintenance costs, and by the availability of better equipment over time.

Mathematical models and analysis methods are used to determine the sequence of these equipment replacement decisions that provides a required service for a specified time horizon in an optimal manner. It is a most common assumption that maintenance and replacement decisions occur on a periodic basis. The decision maker chooses from various options, such as to keep, overhaul, or perform preventive maintenance on the existing asset or replace it with a new/used asset. Any sequence of decisions is called a replacement policy, and any sequence that optimizes some performance measure, such as net present value or annual equivalent cost, is an optimal replacement policy. The equipment replacement problems were started to be taken in to consideration in the early 50's when Alchian, (1953) defined various costs that provide a stream of service as related to the current value of the existing equipment, the net cost of switching to

the new equipment, the cost of replacement at projected intervals, operating costs, and the operating costs of the series of replacements that's going to take place in future where the replacement decisions were based on the present value of these costs with the discounted value of the service stream.

There is an abundance of literature when it comes to various fields in which the replacement analysis is used to solve maintenance or replacement decision models. For instance Bellman, (1955) and Wagner, (1975), were the first to formulate the replacement problem as a dynamic program. They proposed the optimal replacement policies first for the case with no technological change and later under the assumption of technological improvement. Later, Sethi & Chand, (1979) developed a forward dynamic programming model to develop a replacement policy over an infinite planning horizon for several machine replacement models considering an improving technological environment over a period of time. They have also obtained planning horizon results for replacement models with cost minimization, profit maximization, and cost minimization with breakdowns.

Brown, (1991) developed a utility based serial replacement model which was applied on wide range of problems, that explicitly considers risk and tried to avert the risk for the decision maker where the objective is to maximize the expected utilization of a machine whose utility function is not known in advance. He assumed normal distribution for the rewards received from installing and operating an asset over a period of time and developed a dynamic programming model to determine all the possible Pareto-optimal solutions which allows the decision maker to select the preferred alternative without specifying a utility function in advance. Historically, the study of economic equipment replacement is primarily limited to that of a single machining system. The replacement situation whereby the machines under consideration are part of a large

integrated system has received little attention. There are two major difficulties in analyzing such a problem: the interactive nature of an integrated system and the combinatorial nature of replacement alternatives. To attempt this problem Leung & Tanchoco, (1990) came up with a model in which they first disintegrated the production system as a network of centers, and then tackled the multiple equipment replacement decisions as a configuration selection problem. Hence the integrated system is constructed as a network of centers through which multiple commodities flow and the replacement problem is conceived as a configuration selection problem which assesses „if and when' a certain piece or pieces of equipment should be installed in a given configuration. They proposed a model structure which is a multi-stage problem with a set of multi-commodity flow sub-problems at each stage which are formulated as linear programs and then nested into the multi-stage problem formulation as a dynamic program.

There is always a mark of uncertainty present virtually in all the equipment replacement problems which arises due to unknown future events, such as purchase costs, maintenance costs, penalty and inflation. Esogbue & Hearnes, (1998) presented a model to illustrate the use of fuzzy sets and possibility theory to explicitly model uncertainty in equipment replacement decisions via fuzzy variables and numbers especially using fuzzy set approach to calculate the economic life of an asset as well as a finite horizon single asset replacement problem considering multiple challengers. Hartman & Clark presented a model for solving replacement problems and production planning problems simultaneously. Generally replacement problems are solved over a period of long horizons with decisions occurring intermittently for example every quarter or every year, whereas production planning solutions are required daily or weekly, generally resulting in shorter planning horizon models. Thus to address the difficulties arising in combining these two models due to the difference in the frequency with which the two decisions

are made, the authors combined a parallel replacement model to determine optimal keep and replace decisions for groups of assets and a capacitated lot-sizing model to determine periodic production and inventory quantities respectively. While these models are solved separately, the capacity and cost definitions of the system required by the lot-sizing model are dynamically determined through the replacement problem. Thus replacement model is used to determine a sequence of keep and replace decisions for each asset over the horizon in order to minimize purchase, operating costs, and salvage costs over time whereas the production planning decisions aim at minimizing production costs, that include set-up and variable production and inventory costs. Later Hartman, (2000) developed an integer programming formulation for a deterministic, parallel replacement problem in which a number of assets are required for operations in each period over a finite horizon of length T which considers both fixed and variable replacement costs, capital budgeting, and demand constraints where the objective was to minimize discounted purchase and operation costs and maintenance costs less salvage values.

The replacement of a capital asset is generally motivated by deterioration of the asset itself or the introduction of more technologically advanced assets in the marketplace, leading to cost reductions through productivity enhancements. To assure continued production and economical operations, the timely replacement of this equipment is critical. Furthermore, determining the economic life (replacement age and/or cumulative utilization level) can be difficult as randomness in operations may lead fluctuations in utilization. To address this problem Hartman, (2001) presented a stochastic dynamic programming formulation to solve the equipment replacement problem assuming probabilistic asset utilization. While traditional models assume that the state of an asset is defined by its age or operating state, this model defines an asset’s state by age and cumulative utilization. Thus the author presented a case where

the utilization level of the asset was probabilistic and thus the resulting state of the asset, defined by both age and cumulative utilization, was also probabilistic.

The optimal time to replace an asset is highly dependent on how the asset is placed into use over its period of utilization. Traditionally solutions in replacement analysis assume a given level of utilization in each period. However, if multiple assets are available to meet demand and the assets must not continually operate at their maximum capacity, then one may influence the individual utilization patterns by allocating work among the assets. This, in turn, effects the optimal replacement time of each asset. Hartman, (2004) presented dynamic programming model to examine optimal replacement and utilization schedules for a number of assets over a finite horizon with stochastic demand and gaining some insight into optimal decisions under different cost assumptions. Since the asset's utilization is also a variable, both age and cumulative utilization were considered as state variables for replacement decisions.

Later, Childress & Cohen, (2005) presented a dynamic programming formulation for the stochastic parallel machine replacement problem as a set of independent Markovian processes and have shown that under the assumption of an increasing failure rate the structure of optimal replacement policies for the deterministic parallel machine replacement problem extends to stochastic version of the problem. Furthermore they also proved that optimal policies for the stochastic parallel machine replacement problems with arbitrary replacement cost functions satisfy a result analogous to the older cluster replacement rule and moreover they also concluded that replacement decisions are indeed driven by marginal costs, and not by the economies of scale as assumed in most of the parallel machine replacement problems. Espiritu & Coit, (2007) presented an integrated iterative methodology combining dynamic programming and integer programming model to determine replacement schedules for the system composed of

heterogeneous components subject to annual budget constraints limiting total expenditures for maintenance and replacement costs, thus limiting the selection of component replacement schedules. In this research they first formulated a dynamic program to solve for each individual component in the system without consideration of the other components in the system to obtain the optimal replacement schedules for each individual component in the system separately and the objective is to minimize the Net Present Value (NPV) of all components costs over the planning horizon. Then two different integer programming models are also applied in which the first integer programming model is used to determine whether a feasible solution can be obtained while the second integer programming model is to find the recommended component replacement schedules for the components in the system which are nothing but the solution with the minimum cumulative discounted cost. They applied this method in the replacement analysis of a radial electricity distribution system which is commonly used in rural areas.

Replacement problems are usually solved using dynamic programming, but the state space becomes very large even for small parallel machine replacement problems. Yano, (1984) demonstrated the equivalence of a parallel equipment replacement problem with the capacitated facility location problem and further suggested ways in which the techniques and results can contribute to the development of better solution techniques for equipment replacement. Karabakal *et al.,* (1994) solved a different multiple equipment replacement problem where replacement decisions are linked through a budget constraint rather than a fixed cost. And also presented their research work on the type of replacement problems in which the cash flows of a future asset did not depend on the service conditions of a future asset's time of installation, nor the previous replacement decisions. They formulated the finite horizon, deterministic version of the Capital Rationing Replacement Problem as a zero-one integer program and also developed a

branch-and-bound algorithm based on the Lagrangian relaxation method. The replacement schedules for individual assets were determined such that the NPV of the cash flows resulting from the schedules are optimized and also budget constraints imposed for each time period within the planning horizon are satisfied.

Nair & Hoppr, (1992) presented a dynamic programming model to find the optimal equipment replacement decision using a forecast horizon approach taking into account the change in technology. This model was an extension of Hopp & Nair, (1991) to the equipment replacement case where not only the technological forecasts were non-stationary in time, but also the revenue and cost functions were considered as non-stationary in time. Létourneau *et al.*, (1999) developed a method to predict an aircraft component replacement using data mining techniques. Aircraft sensors generate vast amounts of data, much of which languishes in storage after its initial analysis. The authors have developed an approach that uses this data to build models that predict when to replace various aircraft components before they fail. They have implemented these models in a flight-data monitoring system, which receives input in the form of real-time data and outputs alerts when to replace that particular component thus improving airline's overall operations by increasing safety, reducing delays and maintenance costs, and helping managers better plan maintenance activities. The authors have implemented this approach using the SAS system and MLC++ and used it to evaluate the performance of various learning algorithms for different aircraft components.

Rajagopalan (1998) presented a method which combines the equipment replacement literature, which generally ignores changes in demand for equipment and scale economies and the capacity expansion literature, which on the other hand, ignores the replacement feature. Here Rajagopalan, (1998) formulated and solved a general deterministic model which allows

replacement of capacity as well as expansion and disposal to adapt to arbitrary demand changes, and also it permits economies of scale in capacity purchases. This model also partially captures deterioration and obsolescence effects by permitting operating or maintenance costs and salvage values to vary as a function of age.

Conclusions:

In the present chapter a brief overview of component replacement analysis is presented. Also two prominent types of replacements namely Serial Replacement and Parallel Replacement are discussed in detail. The present research focuses on parallel replacement analysis of components involved in power distribution system; hence a thorough literature review is presented in the applications section of the chapter explaining how replacement analysis combined with various heuristic methods can come handy to solve various NP hard and combinatorial complex problems existing in the real world scenario. The knowledge gained from the literature review in component replacement analysis will be used to address the similar kind of replacement problems in the current research of power distribution systems. In the next chapter of this thesis, the electricity transmission and distribution systems are discussed in detail which would help us to form basis to solve the replacement analysis problem for the components involved in the power distribution system.

Chapter 3

ELECTRICITY TRANSMISSION AND DISTRIBUTION NETWORK

3.1 Introduction:

Electric power is essential to modern society. Economic prosperity, national security, and public health and safety cannot be achieved without reliable power supply in the form of electricity. Communities that lack electric power, even for short periods, have trouble meeting basic needs for food, shelter, water, law, and order. Electricity is an integral part of our day to day lives and it is a basic and one of our most widely used forms of energy. It is indispensable to factories, commercial establishments, homes, hospitals, educational institutions and certain modes of transportation and we use electricity to accomplish many tasks on our daily basis – from lighting and heating/cooling our homes, to powering our televisions and computers. Lack of electricity not only causes inconvenience, but also economic loss due to reduced commercial and industrial production. Hence the primary objective of an Electric Power System is to provide electricity to the customers and satisfy the required needs as economically and reliably as possible with a reasonable assurance of continuity and quality Billinton & Allan, (1996 and 1998).

Basically electricity is the flow of electrical power or charge and it is most widely used forms of energy. Electricity is actually a secondary energy source, also referred to as an energy carrier which means that we get electricity from the conversion of other sources of energy, such as coal, nuclear, or solar energy. These are called primary sources. The energy sources we use to make electricity can be renewable or non-renewable, but electricity itself is neither renewable nor nonrenewable. Many scientists and inventors have worked to decipher the principles of electricity since the 1600s. Some notable accomplishments were made by Benjamin Franklin,

Thomas Edison, and Nikola Tesla. Benjamin Franklin demonstrated that lightning is electricity whereas Thomas Edison invented the first long-lasting incandescent light bulb and Nikola Tesla pioneered the generation, transmission, and use of alternating current (AC) electricity, which reduced the cost of transmitting electricity over long distances.

According to the U.S. Department of Energy, in 1940, 10% of energy consumption in United States was used to produce electricity, this fraction was increased to 25% in 1970 and currently it is 40%, showing electricity's growing importance as a source of energy supply. It further states that, electricity grid is one of the largest and most capital-intensive sectors of the economy. Total asset value is estimated to exceed $800 billion, with approximately 60% invested in power plants, 30% in distribution facilities, and 10% in transmission facilities.

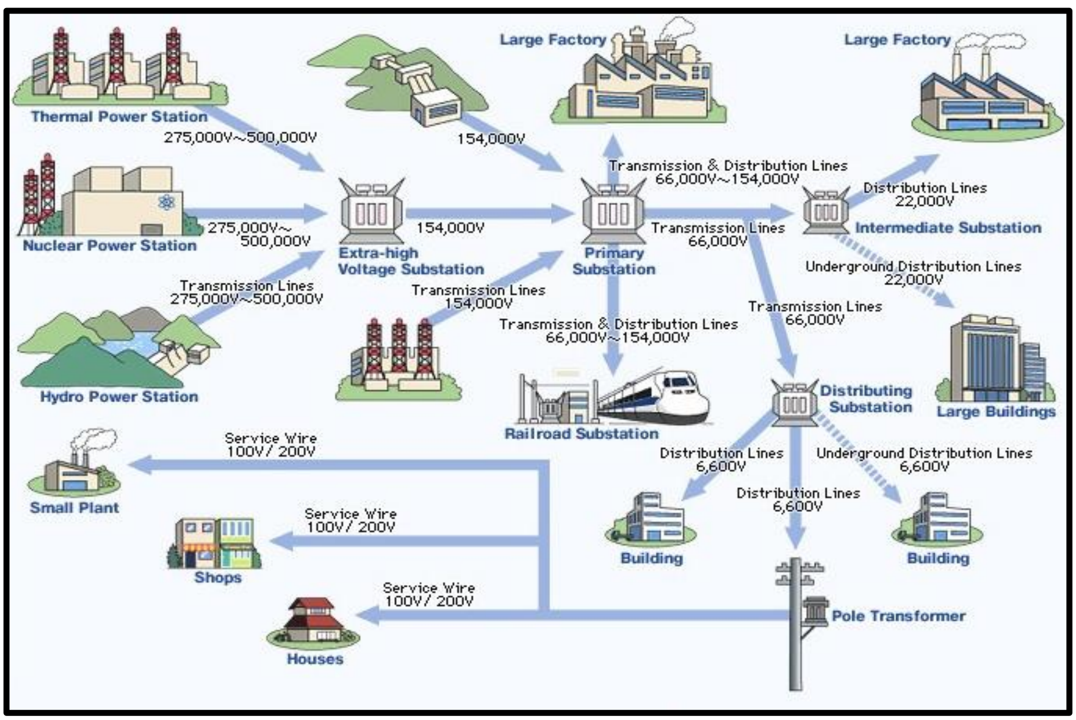

Figure 1: Structure of Electricity Power Supply Network

The power grid basically consists of 3 divisions namely, the generating station, transmission network, and distribution network. As shown in the Figure 1, electricity is produced at lower

voltages at generators from various fuel sources, such as nuclear, coal, oil, natural gas, hydro power, geothermal, photovoltaic, etc. The electricity generated in a power plant must be transformed to higher voltages, which are more efficient for long-distance transmission. Transmission is accomplished by an extensive network of high-voltage power lines, including overhead wires and underground and submarine cables. The electricity is “stepped up” to higher voltages for transportation in bulk over long distance transmission lines through transmission networks. The voltage level of the electricity is eventually “stepped down” before delivering it to the consumers through a local sub-station which comprises of distribution network. The focus of the present paper is in the electricity distribution system. The distribution system is an important part of the total electrical supply system, as it provides the final link between a utility’s bulk transmission system and its customers. The distribution system is generally considered to begin at the substation and end at the customer's meter. It has been reported that 80% of all customer interruptions occur due to failures in the distribution systems Choudary & Koval, (1998).

The cost of a major power outage confined to one state can be on the order of tens of millions of dollars. If a major power outage affects multiple states, then the cost can exceed 100 million dollars. Like for an instance the blackout of New York City and the most of the states in the Northeast, in 1965, which was caused by the events taking place hundreds of miles away. It was a significant disruption in the supply of electricity affecting Ontario in Canada and Connecticut, Massachusetts, New Hampshire, Rhode Island, Vermont, New York, and New Jersey in the United States leaving 30 million people without electricity for up to 12 hours. Similar major power outage took place in 1977 which was localized to New York City only which left the people with electricity blackout for more than 18 hours. And the most recent one is the Northeast Blackout of 2003 which was a massive widespread power outage that occurred

throughout parts of the Northeastern and Midwestern United States and Ontario, Canada. The power was not restored for 4 days in some parts of the United States and in parts of Ontario suffered rolling blackouts for more than a week before full power was restored. Data shows, the outage affected an area with an estimated 50 million people and 61,800 megawatts (MW) of electric load in the states of Ohio, Michigan, Pennsylvania, New York, Vermont Massachusetts, Connecticut, New Jersey and the Canadian Province of Ontario. And an estimated total costs in the United States range between $4 billion and $10 billion [56].

Providing reliable electricity is an enormously complex technical challenge, even on the most routine schedule. It involves real-time assessment, control and coordination of electricity across an interconnected network of transmission lines, and ultimately delivering the electricity to millions of customers by the means of distribution network. The power system is vulnerable to system abnormalities such as control failures, protection or communication system failures, and disturbances, such as lightning, and human operational errors Liu *et al*., (2000). Therefore, maintaining a reliable power supply is a very important issue for power systems design and its operation.

3.2 Introduction to Electric Power Systems:

In this section various subsystems involved in Electric Power Systems namely Generation, Transmission and Distribution Systems are explained briefly which will help us lay the basic foundation in understanding how electricity is generated and transformed before it reaches the end user.

3.2.1 Electricity Generation

The electric utility industry can trace its beginnings to the early 1880's. During that period several companies were formed and installed water-driven generation for the operation of the arc lights for street lighting; the first real application for electricity in the United States. Power generating plants like any other manufacturing plants, process raw materials into useful products; in this case the product is electrical energy. Electricity is most often generated at a power station by electro-mechanical generators, primarily driven by heat engines fueled by chemical combustion or nuclear fission but also by other means such as the kinetic energy of flowing water and wind. There are many other technologies that can be used to generate electrical energy such as solar photovoltaic cells and geothermal power. As demonstrated by the schematic arrangement shown in Figure 2, generally in the larger central generating plants, fossil or nuclear energy (in the form of fuel) is first converted into heat energy (in the form of steam), then into mechanical energy (in an engine or turbine), and finally into electrical energy (in a generator) to be transmitted over the high tension transmission lines to be utilized by the end consumer Pansini & Smalling, (2002).

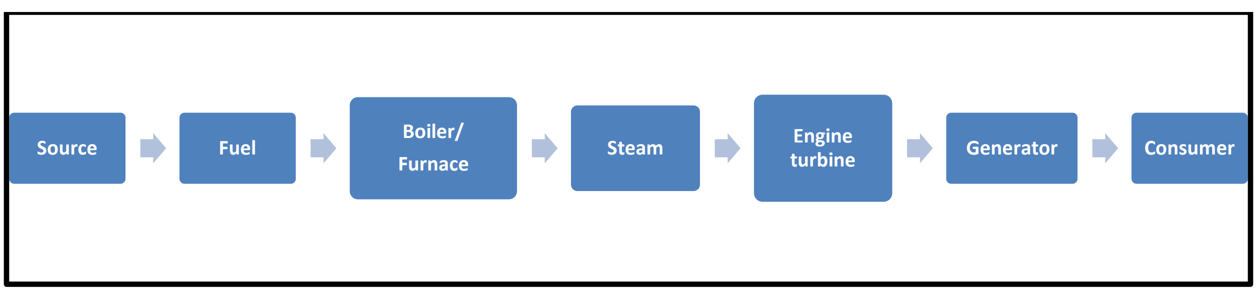

Figure 2: Schematic Diagram of Energy Conversion

Most commonly, electricity is produced by burning of fossil fuel (Coal, Oil or Natural Gas) in the furnace of a steam boiler. Steam from the boiler drives a steam engine or turbine connected by a drive shaft to an electrical generator which is finally transported to the end consumers.

3.2.1.1 Sources of Energy:

Statistics provided by U.S. Energy Information Administration states that about 90% of U.S. electricity is generated by three fuels: Coal, Natural Gas and Nuclear energy. Coal is the most common source of energy for generating electricity in the United States. Natural gas, in addition to being burned to heat water for steam, can also be burned to produce hot combustion gases that pass directly through a turbine, spinning the turbine's blades to generate electricity. Gas turbines are commonly used when electricity utility usage is in high demand.

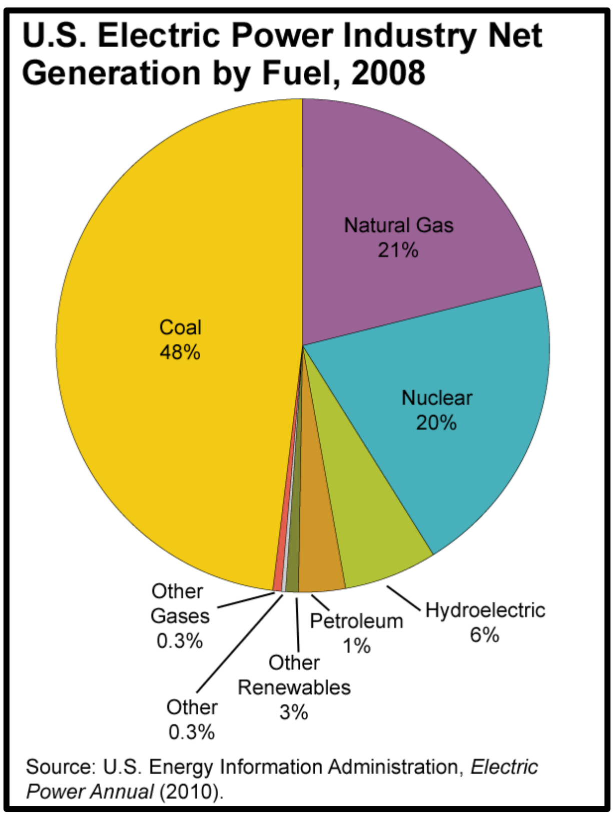

Figure 3: U.S. Electric Power Industry Net Generation by Fuel, data for 2008

Petroleum can be burned to produce hot combustion gases to turn a turbine or to make steam to turn a turbine. Residual fuel oil, a product refined from crude oil, is often the petroleum product used in electric plants that use petroleum to make steam. Nuclear power plants provides about one-fifth of electricity requirement in United States. Nuclear power is a method in which steam is produced by heating water through a process called nuclear fission. Natural resources such as coal, petroleum, oil and natural gas take thousands of years to form naturally and cannot be replaced as fast as they are being consumed.

3.2.1.2 Types of Generation

Many types of generating plants are in use and possible for the future, including steam plants fueled by non-renewable natural resources like coal, oil and natural gas, nuclear plants and plants which use renewable resources such as hydro power plants, solar energy, wind energy and geothermal energy. Most types of electric generating units can be grouped by prime mover which is a type of device that drives the electric generator. The most common types of prime movers used in the industries are:

a) Steam Turbine;

b) Combustion (Gas) Turbine; and

c) Reciprocating Engines

Different fuels may be used for the various types of primer movers. The source of heat can be from the burning of coal, oil, gas or the heat given off in the nuclear reactor.

a) Steam Turbines:

In a steam turbine generating plant fossil fuels (coal, oil and natural gas and nuclear energy) are burned in a furnace. In a nuclear power plant, a reactor contains a core of nuclear fuel, primarily uranium. When atoms of uranium fuel are hit by neutrons, they fission (split) releasing heat and more neutrons. Under controlled conditions, these other neutrons can strike more uranium atoms, splitting more atoms, and so on. Thereby, continuous fission can take place, creating a chain reaction releasing heat. The heat is used to turn water into steam that, in turn, spins a turbine that generates electricity. Thus in a nuclear plant, heat is produced as a result of a nuclear chain reaction and the heat given off by this combustion is used to heat water in a boiler to such a temperature that steam is produced. The steam is then passed through one or more turbines. Energy contained in the steam is extracted by allowing the steam to expand and cool as it passes through the turbines. This energy turns the blades of the turbine, which are connected to shaft. This shaft is connected to the electric generator and rotates the coils of the magnetic field of the generator, thus producing electricity. Nuclear power was used to generate about 21% of all the Country's electricity in 2008.

b) Combustion (Gas) Turbines:

Combustion turbines are most often fueled by gas but can be fueled with some liquids as well. In a combustion turbine hot gasses burn, are expanded through a turbine, driving a generator. An additional component of a combustion turbine is a compressor. This device increases the pressure of the air used in the combustion section by a factor of approximately 10. When the air is compressed in this manner, its temperature is increased. The resulting combustion raises the temperature of the gas which is then passes through a turbine, where it is cooled and expanded.

The dissipated energy turns the turbine, which in turn, runs an electrical generator thus producing electricity.

c) Reciprocating Engines:

This type of generation usually consists of a large diesel engine which uses diesel fuel as a source of energy. Electricity is produced by connecting the output shaft of the engine to an electrical generator. Diesel engine improvements have resulted in considerable reductions in weight and improvement in efficiency.

3.2.1.3 Other forms of Generation:

There are other methods of producing electric power that currently contribute only small amounts of total electric power production. These types of generation use renewable sources of energy such as Solar Energy, Hydropower Energy, Wind Energy, Geothermal Energy, and Energy produced through Biomass.

Solar power is derived from energy from the sun. Sunlight can be converted into electricity using photovoltaic (PV) and solar-thermoelectric plants. PV conversion produces electricity directly from sunlight in a photovoltaic solar cell. Solar-thermal electric generators concentrate solar energy to heat a fluid and produce steam which is used to drive turbines thus generating electricity.

Hydropower is a process in which gravitational force of falling or flowing water is used to spin a turbine connected to a generator. It is most widely used form of renewable energy and also most eco-friendly method of generating electricity with practically no direct wastes and very low output level of greenhouse gas carbon dioxide compared to any other methods of power

generation using non-renewable resources Kabisama H. W., (1993). There are two basic types of hydroelectric systems that produce electricity. In the first and most common system, uses the potential energy of water stored in the dam which in turn is used to drive the water turbine and thus the generator. In this method, flowing water is first accumulated in reservoirs created by dams. The water falls through a pipe called a penstock and applies pressure against the turbine blades to drive the generator to produce electricity. In the second system, called run-of-river, water is diverted from a river using a relatively low dam or weir into penstocks and turbines. Run-of-river power plants are more dependent on river flows than hydro plants with reservoirs for storing water which can produce electricity even when natural river flows are low.

Wind power is produced by converting wind energy into a useful form of energy, such as using wind turbines to make electricity. This is executed with the use of wind turbine. A wind turbine is a rotary device which uses mechanical energy of the flowing wind to generate electricity. Electricity generation from wind has increased significantly in the United States since 1970, but wind power remains a small fraction of U.S. electricity generation, about 1%.

Geothermal power comes from heat energy buried beneath the surface of the earth. This geothermal energy originates from the original formation of the planet, from radioactive decay of minerals, from volcanic activity beneath the surface of earth and solar energy absorbed by the surface of earth. In some areas, enough heat rises close to the surface of the earth to heat underground water into steam, which can be tapped for use at steam-turbine plants. Geothermal power is cost effective, reliable, sustainable, and most importantly its environmentally friendly.

Biomass is material derived from plants or animals (i.e. biogenic) and includes lumber and paper mill wastes; food scraps, grass, leaves, paper, and wood in municipal solid waste; and

forestry and agricultural residues such as wood chips, corn cobs, and wheat straw. These materials can be burned directly in steam-electric power plants, or converted to gas that can be burned in steam generators, gas turbines, or internal combustion engine-generators.

Once the electricity is generated, it needs to be transported to the final customer; this transportation of the bulk electricity from the generation station to the final customer is performed by the electricity transmission network which finally reaches the customer through electricity distribution network as explained in the new sections of this chapter.

3.2.2 Electricity Transmission

The purpose of the electric transmission system is the interconnection of the electric energy producing power plants or generating stations with the loads. The transmission systems are unique because they are designed to move this energy at the speed of light from the generator to the consumer since there is no long term storage capability for electricity. Transmission is the means by which large amounts of power are moved from generating stations where this power is produced, to substations from which distribution facilities transport the power to customers. They can carry alternating current or direct current or a system can be combination of both. All transmission lines carry three-phase current, or three separate streams of electricity traveling along three separate conductors as shown in Figure 4. Electricity is usually transmitted at high voltages to reduce the energy lost in long distance transmission. Transmission lines are also used to provide connections to neighboring systems.

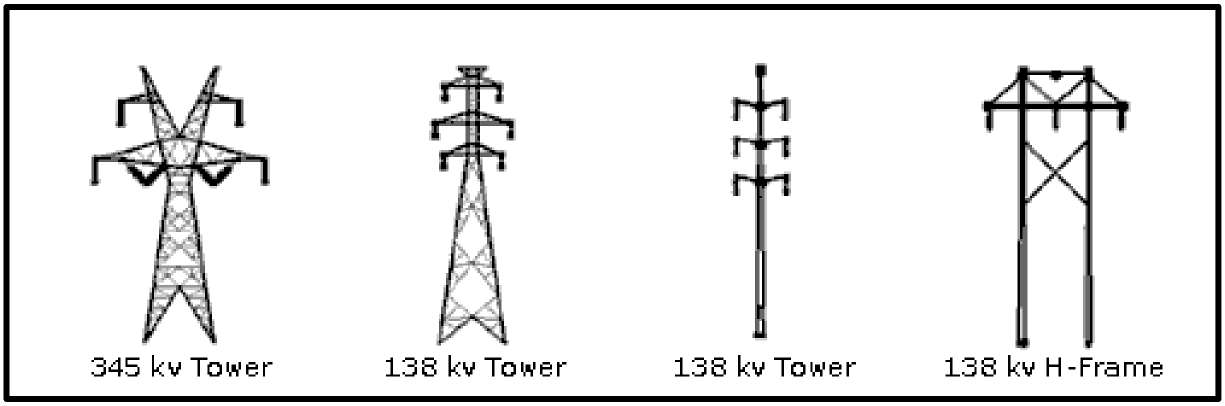

Figure 4: Different types of transmission lines

Mostly a transmission system is interconnected with transmission systems of other electricity providers thus forming a high voltage transmission network commonly known as power grids. In the US, these are typically referred to as power grids or simply grid. Typically the transmission system consists of three-phase transmission lines and their terminals called substations or switching stations. Transmission lines can be either overhead, underground or sub marine. There are high-voltage alternating current (HVAC) lines and high-voltage direct current lines (HVDC).

3.2.2.1 Overhead Transmission:

An overhead transmission line is a very complex, continuous, electro-mechanical system which is used to transport power safely from a circuit breaker on one end to the circuit breaker on the other end. The overhead AC transmission lines share one characteristic that they carry 3-phase current. The voltages vary according to the particular grid system which they belong to and the transmission voltages vary from 69kv up to 765kv. Figure 5 below shows examples of different overhead transmission lines structures most commonly found in our city perimeters;

Overhead power transmission lines are classified in the electrical power industry by the range of voltages:

- Low voltage – less than 1000 volts, used for connection between a residential or small commercial customer and the utility.
- Medium voltage (Distribution) – between 1000 volts (1 kV) and to about 33 kV, used for distribution in urban and rural areas.
- High voltage (Sub-transmission if 33-115kV and transmission if 115kV+) – between 33kV and about 230 kV, used for sub-transmission and transmission of bulk quantities of electric power and connection to very large consumers.
- Extra High Voltage (Transmission) – over 230 kV, up to about 800 kV, used for long distance, very high power transmission.
- Ultra High Voltage – higher than 800 kV.

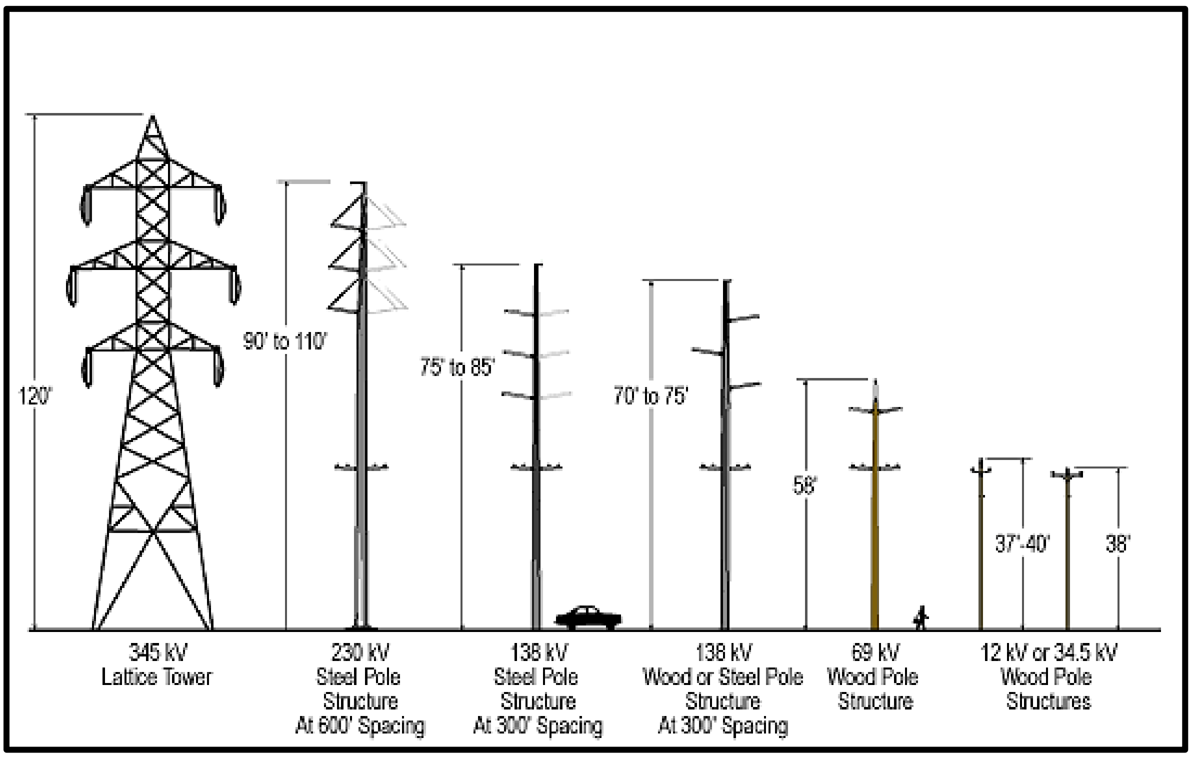

Figure 5: Some typical overhead transmission line structures

It is physically composed of many individual components made up of different materials having a wide variety of mechanical properties but the primary components of an overhead

transmission lines are conductors, ground or shield wires, insulators, support structures and land. Conductors are the wires through which the electricity passes. Transmission wires are usually of the aluminum conductor steel reinforced type, made of stranded aluminum woven around a core of stranded steel which provides structural strength. When there are two or more of these wires per phase, they are called bundled conductors. Ground or shield wires are wires strung from the top of one transmission tower to the nest, over the transmission line. Their function is to shield the transmission lines from lightning strikes.

Insulators are made of materials which do not permit the flow of electricity. They are used to attach the energized conductors to the supporting structures which are grounded. The higher the voltage at which the line operates, the longer the insulator strings. In recent years, polymer insulators have become popular in place of the older, porcelain variety. They have the advantage of not shattering if struck by a projectile. The most common form of support structures for transmission lines is a steel lattice tower. In recent years, as concern about the visual impact of these structures has increased, tubular steel towers also have come into use. The primary purpose of the support structure is to maintain the electricity carrying conductors at a safe distance from ground and from each other. Higher voltage transmission lines require greater distances between phases and from the conductors to ground than lower voltage lines and therefore they require bigger towers. The clearance from ground of the transmission line is usually determined at the midpoint between two successive towers, at the low point of catenary formed by the line.

3.2.2.2 Underground Transmission:

Underground transmission lines are more common in populated areas. It's common today to see lower-voltage distribution lines that connect to homes and businesses buried directly in the

ground using less invasive construction methods. Electric power can be transmitted by underground power cables instead of overhead power lines. This kind of underground transmission is very common in the urban areas with dense population. Areas where there is scarcity of land availability for overhead structures or planning consent is difficult to undertake. When there is a river and/or other natural obstacles like some other water bodies or mountains.

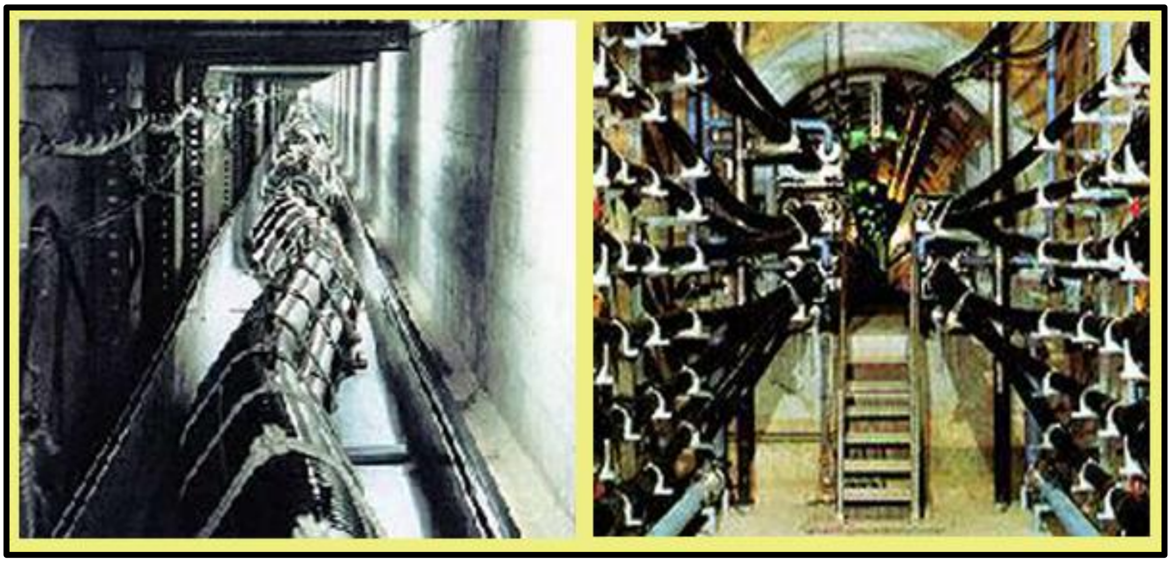

Figure 6: Underground transmission through tunnel

The underground transmission can assist the transmission of electric power across the areas of significant or prestigious infrastructural development and land with outstanding natural or environmental heritage. This kind of transmission is also recommended for land whose value must be maintained for future urban expansion and rural development. Furthermore placing transmission lines underground is a practice generally used only when there is no viable overhead corridor. However, high-voltage transmission lines require greater infrastructure. They may be buried with no protection, or placed in conduit, trenches or tunnels. As shown in Figure 6, when transmission lines are installed in a tunnel, this enables many circuits in a limited area. Heat is generated when electricity flows through cables, limiting the power transmission capacity

in tunnels. Usually a tunnel cooling system is installed which circulates cold water through the tunnels to increase the capacity of the transmission lines.

Figure 7: Underground transmission through trenches

Most cities use underground cables to distribute electrical energy. These cables virtually eliminate negative environmental effects and reduce electrocution hazards. However, they incur higher construction costs because the cost of burying cables at transmission voltages is several times greater than overhead power lines. Another disadvantage would be the repair time, the repair time is usually high and also the fault finding is time consuming too. However this problem can be tackled by laying a redundant line but these may increase the maintenance cost associated with underground transmission lines. Apart from these disadvantages they also have some critical advantages over other conventional modes of power transmission for an instance they are subjected to less damage from severe weather conditions such as lightning, wind and extreme cold weather to a level of freezing. They have significantly reduced amount of emission into the surrounding area, of electromagnetic fields because all electric currents generate electromagnetic flux but the shielding provided by the earth surrounding underground cables restricts their range and power. And moreover underground cables need a narrower surrounding

strip of about 1-10 meters to install whereas an overhead transmission line requires a surrounding strip of about 20-200 meters wide to keep it permanently clear for safety, maintenance and repair activities.

Another type of underground transmission is the transmission through submarine cables. High-voltage cables are frequently used for crossing large bodies of water. Water provides natural cooling, and pressure reduces the possibility of void formation. A typical submarine cable has cross-linked polyethylene insulation, and corrosion-resistant aluminum alloy wire armoring that provides tensile strength and permits installation in deep water. Submarine cables are usually laid underwater in trenches with the distance between each phase measured in feet. A major consideration is to have the trench deep enough so that the cables are not damaged by anchors or fishing trawlers. The environmental impacts of dielectric fluid leaks from damaged cables are a concern and also another concern is the need for a long length of a spare cable to facilitate repairs in the event of damage or failure.

Underground cables are divided into two categories: distribution cables (less than 69 kV) and high-voltage power-transmission cables (69–500 kV).

There are four main types of underground transmission lines, which include:

a) High pressure, fluid filled pipe (HPFF)

HPFF pipes are the most common in the U.S. Each pipe consists of a single steel pipe with three, high-voltage, aluminum or copper conductors inside surrounded by dielectric oil at 200 psi. Each conductor is insulated with oil impregnated paper, and covered in a metal shielding.

b) High pressure, gas-filled pipe (HPGF)

A HPGF pipe is similar to the fluid-filled pipe with the exception of the dielectric oil, which has been replaced with nitrogen.

c) Self-contained fluid-filled (SCFF)

SCFF pipes are often the choice for underwater installations. These hollow conductors are filled with an insulating fluid, wrapped with an insulating paper, followed by a metal sheath and plastic coating. These are not placed together in a pipe for installation, and remain independent.

d) Cross-linked polyethylene (XLPE)

In the XLPE, also called a “solid dielectric” transmission line, a solid dielectric material replaces the pressurized liquid or gas described in the previously. These are not installed in a bundle, rather each conductor; surrounded by a semi conductive shield, cross-linked polyethylene insulation, and a metallic shield and plastic coating; is set individually in a concrete track.

3.2.3 Electricity Distribution:

The distribution system is that portion of the electric power system which has the greatest direct impact on the level of reliability experienced by the consumer Billinton & Wang, (1998). Once the substation lowers the voltage, the electricity is ready to be transported to homes and businesses through a distribution, or networks, system. The primary function of the distribution system is to connect the electric bulk power system to customers requiring service at voltages below that of the transmission and sub-transmission systems. The distribution system is the portion of the electric power system most readily seen by the customer and which contributes most directly to providing electric service. Of the three primary functions of the electric utility,

generation, transmission, and distribution, the distribution system plays the largest role in the quality of service received by the consumers.

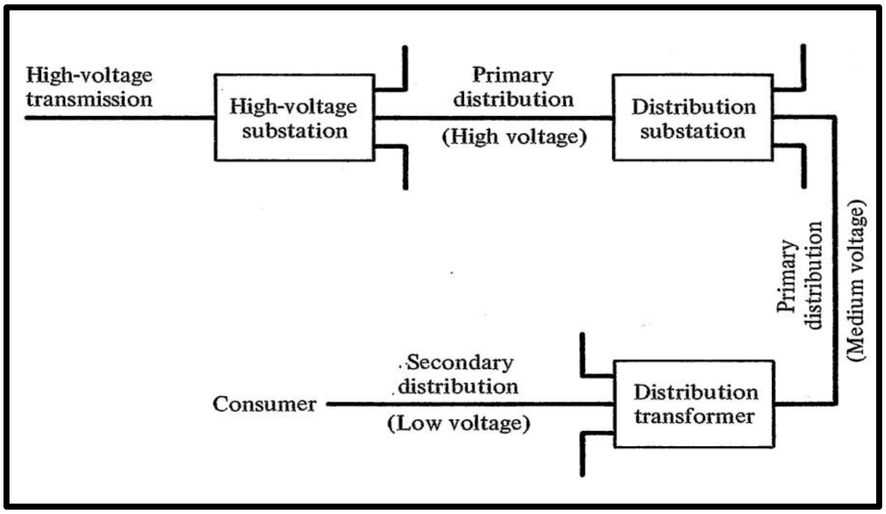

Figure 8: The basic distribution system

Source: Electric Power Transmission Systems, Eaton & Cohen, (1983)

As shown in Figure 8, the primary components of a distribution system are:

- Distribution Substation;
- Primary Feeder;
- Distribution Transformer;
- Secondary lines and services.

The distribution substation receives electric power directly from the transmission or sub-transmission system and converts it to a lower voltage for use on a primary distribution feeder. In a common configuration a distribution substation may have several transformers and a number of primary distribution feeders emanating from it. The distribution network consists of the poles

and wires that can be seen in the streets of cities and towns or in residential areas. Conductors called feeders reach out in all directions from the substation carrying electricity.

The distribution transformer, usually on a pole, is supplied by the primary distribution feeder and transforms the voltage of the primary feeder from the voltage ranges of (2400 volts through 34,500 volts) to a lower voltage most commonly used by consumers. The secondary lines and service connections provide electric service directly to the ultimate consumer at the lower voltages produced at the output terminals of the distribution transformers.

Primary voltage in the 13kV class is predominant among United States utilities. The 4kV class primary systems are older and are gradually being replaced. In some areas 34kV is used in new, high density load areas. The three-phase, four-wire primary system is the most widely used. Under balanced conditions, the voltages of each phase are equal in magnitude and 120 degrees out of phase with each of the other two phases.

Rural and suburban areas are usually served by overhead primary lines, with distribution transformers, fuses, switches and other equipment mounted on poles. Urban areas with high density loads are served by underground cable systems, with distribution transformers and switchgears installed in underground vaults or in ground level cabinets.

Distribution transformers are of several types:

- Single phase or three phase;
- Pole mounted or pad mounted;
- Underground.

They come in various sizes explained in the further sections and also they can be purchased with various efficiencies and specifications.

Secondary distribution delivers energy at customer utilization voltages from distribution transformers to meters at customers' premises. To supply high-density load areas in downtown sections of cities, where the highest degree of reliability is needed, secondary networks are used. Such networks are supplied by two or more primary feeders through network transformers. These transformers are protected by devices that open to disconnect the transformer from the network if the transformer or supply feeders are faulted. Smaller secondary networks called spot networks are also used to supply loads requiring extra reliability.

There are many ways of connecting unit substations to the primary distribution system. However the two widely used configurations are:

a) Radial Configuration:

Distribution systems are normally operated as radial networks; however, configuration is changed during operation Baran & Wu, (1989). Radial networks have some advantages over meshed networks such as lower short circuit currents and simpler switching and protecting equipment. On the other hand, the radial structure provides lower overall reliability. Therefore, to use the benefits of the radial structure, and at the same time to overcome the difficulties, distribution systems are planned and built as weakly meshed networks, but operated as radial networks Taleski *et al.,* (1997). A radial configuration provides a single direct path from the high-voltage feeder to the transformer to the load as shown in Figure 9; it is widely used in the area that has low-load density requirements. It is safe, economical, simple to operate, and yet highly reliable due to the high reliability of the equipment. However a failure at any point cuts off service to all points downstream from that point.

b) Interconnected Configuration:

In this configuration pairs of load-center secondary lines are connected together either by cable or by circuit breaker as shown in Figure 9, a load may thus be supplied from one of two sides thus providing greater flexibility than the radial configuration and thus allowing the removal of certain pieces of equipment for repair or maintenance activities without interrupting the service.

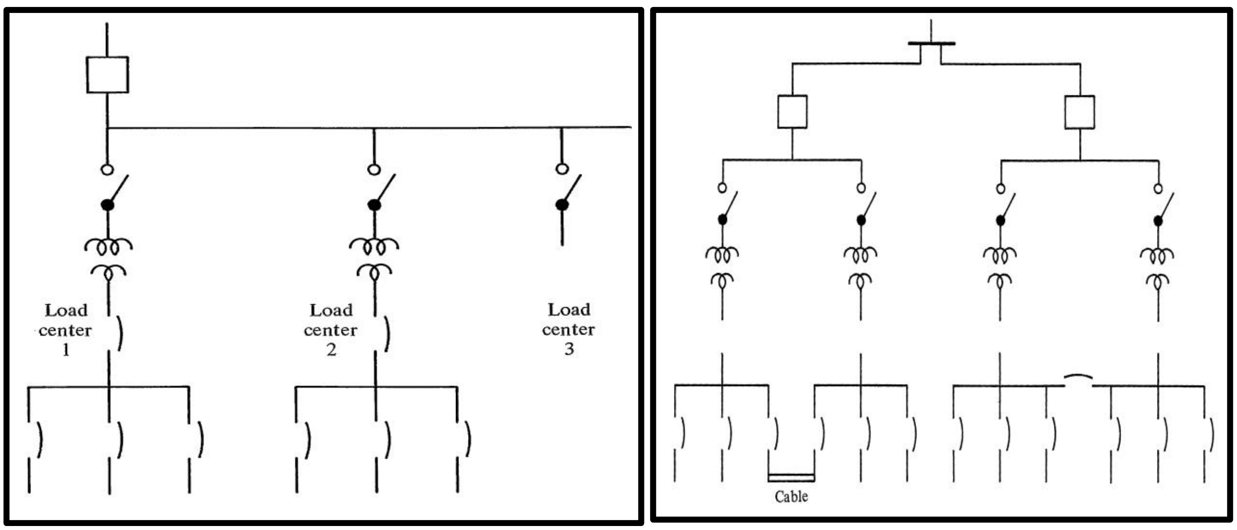

Figure 9: Radial and Interconnected Distribution Configuration

Source: Electric Power Transmission Systems, Eaton & Cohen, (1983)

3.2.3.1 Substations:

A substation is a high-voltage electric system facility. It is used to switch generators, equipment, and circuits or lines in and out of a system. It also is used to change AC voltages from one level to another, and/or change alternating current to direct current or direct current to alternating current. Some substations are small with little more than a transformer and associated switches. Others are very large with several transformers and dozens of switches and other equipment.

Figure 10: A typical distribution substation

Substations are locations where transmission lines are tied together. They fulfill a number of functions.

- They allow power from different generating stations to be fed into the main transmission corridors.
- They provide a terminus for interconnections with other systems.
- They provide a location where transformers can be connected to feed power into the sub-transmission or distribution systems.
- They allow transmission lines to be segmented to provide a degree of redundancy in the transmission paths.
- They provide a location where compensation devices such as shunt or series reactors or capacitors can be connected to the transmission system.
- They provide a location where transmission lines can be de-energized, either for maintenance or because of an electrical malfunction involving the line.

- They provide a location for protection, control, and metering equipment.

There are four main types of substations:

Step-up transmission substations: These substations receive electric power from a nearby generating facility and use a large power transformer to increase the voltage for transmission to distant locations.

Step-down transmission substations: These substations are located at switching points in an electrical grid. They connect different parts of a grid and are a source for sub-transmission lines or distribution lines. This substation can change a transmission voltage to a sub-transmission voltage, usually 69 kV.

Distribution substations: Distribution substations are located near to the end users. Distribution substation transformers change the transmission or sub-transmission voltage to lower levels for use by end-users. Typical distribution voltages vary from 19,920 volts to 2400 volts.

Underground distribution substations: These substations are also located near to the end-users. Distribution substation transformers change the sub-transmission voltage to lower levels for use by end-users.

3.2.3.2 Components in power distribution system:

There are a number of components involved in the electricity transmission and distribution networks. However, there are elements common to all such as;

Bus: This is an electrical structure to which all the lines and transformers are connected. Buses are of two generic types: open air and enclosed. Enclosed buses are used when substations are located in buildings and outdoors where space is at a premium.

Figure 11: Bus bar connected to a distribution circuit

They involve the use of an insulating gas such as sulfur hexafluoride to allow reduced spacing between energized phases. Bus structures are designed to withstand the large mechanical forces that can result from fields produced by high short-circuit currents. These forces vary with the third power of the high short-circuit currents. These forces vary with the third power of the current. A bus section is the part of a bus to which a single line or transformer is connected.

Protective Relays: Relays are the devices that continuously monitor the voltages and currents associated with the line and its terminals to detect failures or malfunctions in the line or equipment. Such failures are called faults and involve contact between phases or between one or more phases and ground. The relays actuate circuit breakers.

Figure 12: An electro-mechanical relay & Microprocessor based digital protecting relay

Circuit Breakers: They are the devices that are capable of interrupting the flow of electricity to isolate either a line or a transformer. They do so by opening the circuit and extinguishing the arc that forms using a variety of technologies such as oil, vacuum or air blast.

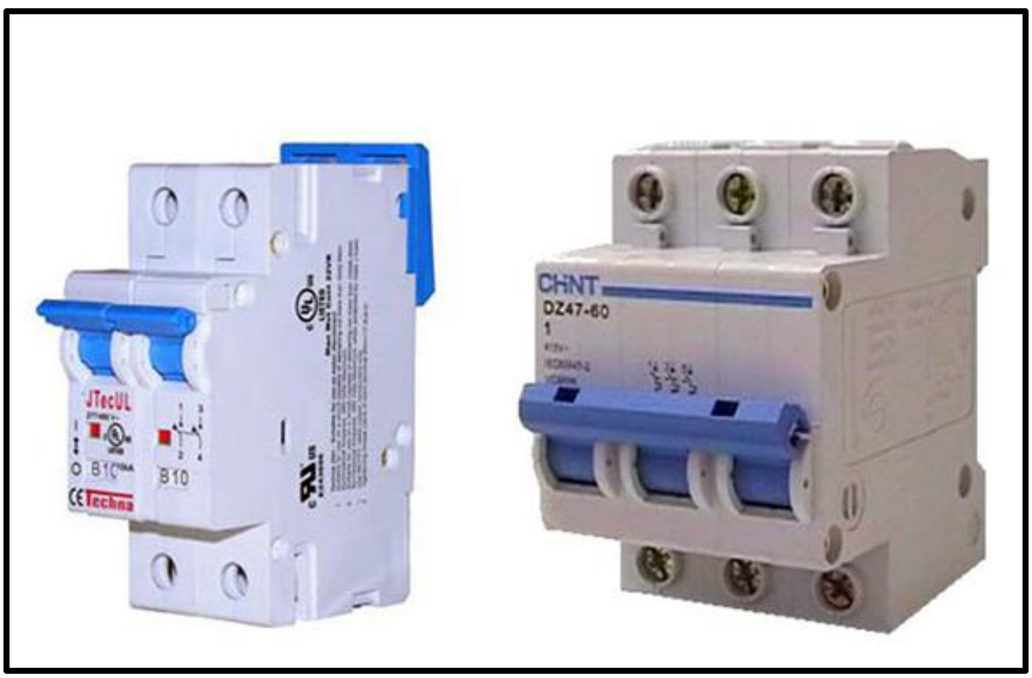

Figure 13: Two and Three pole circuit breakers

Circuit breakers may be installed in series with the line or transformers or may be installed on both sides of the bus section where the line connects. They allow individual lines or transformers

to be removed from service (de-energized) automatically when equipment (protective relays) detects operating conditions outside a safe range. To minimize the impact of electrical shocks to the transmission system, minimizing the total time for the relay to detect the condition and the circuit breaker to open the circuit is a critical design issue. Circuit breakers also allow lines or transformers to interrupt all three phases simultaneously, although in certain special applications, single-phase circuit breakers can be employed, which will open only the phase that has a problem.

Transformers: Transformers are the devices that are used to connect facilities operating at two different voltage levels. For example a transformer would be used to connect a 138kV to a 13kV bus. The transformer connects to all three phases of the bus. Physically the transformers can include all three phases within one tank or there can be three separate tanks, one per phase. Larger capacity units may have three separate tanks because their size and weight may be limiting factor because of transportation issues.

Figure 14: Different types of distribution transformers

Any type of a transformer is an autotransformer, which is used when facilities at nearly the same voltage are to be connected, for example, 138 kV to 115 kV. Rather than having two separate paths for the electricity, connected only by the magnetic flux through the transformer as in a conventional unit, the winding of autotransformer involves a tap on the higher voltage winding which supplies the lower voltage.

Switches: A switch is an electrical component that can break an electrical circuit, interrupting the current or diverting it from one conductor to another. Additionally the switches are also used to open a circuit when only charging current present is due.

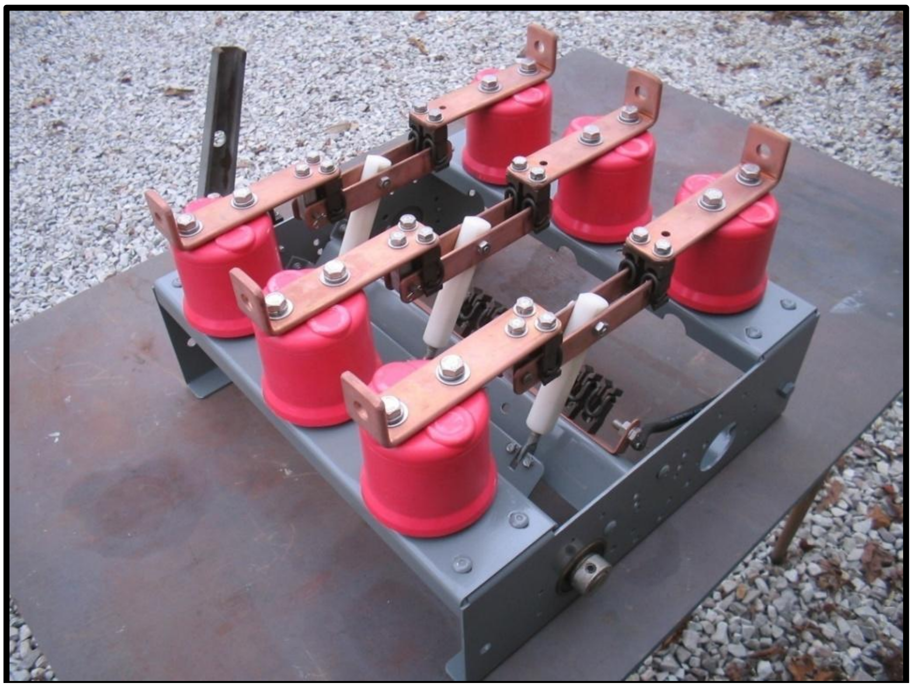

Figure 15: Electrical circuit switch

These are primarily used to connect or disconnect circuit breakers or transformers which are not carrying load current. They are also used in conjunction with circuit breakers to provide another level of safety for workers by inserting a second opening between station equipment out of service for work and the still energized section of line or bus.

In the U.S., there are 10,287 transmission substations and 2,179 distribution substations. Transmission substations use transformers to convert a generator's voltage up to 155kV to 765kV for long distance transmission in order to reduce transmission line losses Albert *et al.*, (2004). The distribution substation steps power down the voltage to distribution levels and splits it into many directions. Thus, substations are very critical component of our distribution system, and a loss of only 4% of transmission substations would result in a 60% loss of connectivity.

Table 1: Type and Number of Equipment Installed at all substations in United States

Equipment	Total Number Installed
Autotransformer	12,151
Oil Circuit Breaker	193,586
Oil Circuit Recloser	7,004
Reactor	422
Transformer	63,797
Vacuum Circuit Recloser	169
Vacuum Circuit Breaker	338
Voltage Regulator	25,443

Note: Totals for all substations within the utility industry based on the assumption of 50,000 totals and extrapolated from Energy data.
Source: U.S. Environmental Protection Agency, Sept 2004.

The electric utility industry is roughly 115 years old, which means, at this age, all of the original equipment in any utility system is now long gone. Thus, it's clear that most utilities managed to deal with equipment aging, wear out and replacement in an effective manner over the past century. And also most of the equipment's are approaching 50 years of age and thus dealing with

the age related problems Brown *et al.,* (2006). The aging infrastructure has higher costs to operate and maintain and, more importantly, lower reliability. As the equipment ages, the component outage rates increase, having an impact on the total system downtime and leading to increased costs to operate Espiritu *et al.,* (2007). Hence there is a need to develop methods which would address this problem of the aging infrastructure and thus help us develop a reliable electricity transmission and distribution networks.

Conclusion:

In the present chapter the functionality of electricity generation, transmission and distribution system is explained in detail. The present research is based mostly on this power systems especially focusing more on the components involved in the power distribution network. Further we can conclude that the economic significance of electricity is staggering. It is one of the largest and most capital-intensive sectors of the economy. Total asset value of this sector is estimated to exceed $800 billion, with approximately 60% invested in power plants, 30% in distribution facilities, and 10% in transmission facilities. Thus creating policies to keep the system working is based on striking a balance between three key drivers: adequate and reliable supply, acceptable electricity prices and environmental sustainability. In the real world scenario, the distribution network encounters a lot of optimization problems and thus it affects the overall reliability of the whole system. Hence a reliable distribution system must be designed to meet future power supply requirements. Thus considerable amount of work has been done in this area of interest. In the present research component replacement analysis problem is solved thus aiming at improving the reliability of the overall system. The objective functions and the variables used will be introduced in the further chapters.

Chapter 4

HEURISTIC OPTIMIZATION METHODS

4.1 Introduction:

In the previous chapter the electric power systems and various aspects of its operation and functionalities was introduced. In the present chapter different methods of optimization techniques will be introduced. The primary focus of this chapter is to understand different types of optimization methods. Various heuristic and meta-heuristic approaches are explained briefly. And the main objective of this chapter is to introduce the Genetic Algorithms (GA's). The later part of the chapter reviews the historical background of GA's including the origin based on the Darwin's theory of evolution and additional features in order to solve complex optimization problems applied in the real world scenarios. Lastly, the characteristics that influenced the choice of GA's for solving the component replacement problems are explained in detail which will help us understand the problem statements that will be introduced in chapter 5.

4.2 Combinatorial Optimization:

In engineering domain, an optimization problem is the problem of finding the best solution from a set of feasible solutions. In the simplest case, this means solving problems in which one seeks to minimize or maximize a real function by systematically choosing the values of real or integer variables from within an allowed set. This formulation, using a scalar, real-valued objective function, is probably the simplest example; the generalization of optimization theory and techniques to other formulations comprises a large area of applied mathematics. More generally, it means finding "best available" values of some objective function given a defined

domain, including a variety of different types of objective functions and different types of domains.

„Combinatorial Optimization' is a term that has emerged in the recent times to describe those areas of the applied mathematical programming that are concerned with the solution of optimization problems having a pronounced combinatorial or discreet structure. However, problems of this nature have been posed since the beginning of mankind. Most often optimization problems have an infinite number of solutions however there exist a decent number of problems which in the real world scenario has only a finite number of solutions. The body of knowledge that's concerned with the theory and techniques for these kinds of problems are called „Combinatorial Optimization'. It operates on the domain of those optimization problems, in which the set of feasible solutions is discrete or can be reduced to discrete, and in which the goal is to find the best solution. Combinatorial optimization is a subset of optimization that is related to operations research and computational complexity theory which has important applications in several fields, including artificial intelligence, mathematics, and software engineering. Hard combinatorial optimization problems appear in a multitude of real world applications, such as routing, assignment, scheduling, cutting and packing, network design, protein alignment, and many other fields of utmost economic, industrial and scientific importance.

Some of the most common and important combinatorial optimization problems are:

- **The Minimal Cost Network Problem**

  Given a network with arc costs and capacities, what would be the minimum cost flow assignment which transports a given commodity from source to sink?

- **The Facilities Layout Problem**

  Given a set of facilities to be laid out on a plane factory floor, what would be the spatial arrangement of these facilities which will maximize the benefit of pairwise adjacency?

- **The Transportation Problem**

  Given a distribution system from a set of warehouses to a set of factories, what would be the least transportation cost assignment of a single commodity satisfying factory production capacity and warehouse demand?

- **The Travelling Salesman Problem**

  Given a set of cities, what circuit of them should a salesman tour in order to minimize total distance traveled if s/he is to visit each city in the set, returning to the starting point?

- **The Vehicle Scheduling Problem**

  Given a set of vehicles to be used for servicing a number of locations, what set of tours should be assigned to the vehicles which minimizes distance traveled and services the locations subject to vehicle capacity?

The given list is not exhaustive or not limited, but it gives an idea about the wide range of areas which are considered to be a complex and hard combinatorial optimization problems.

The techniques used for solving such optimization problems can be classified into two categories: Exact Optimization Methods like Linear Programming, Lagrangian Relaxation Methods, Dynamic Programming, Integer Programming, Branch and Bound and many more. Another category is the Meta-Heuristics Approach. Meta-heuristic algorithms are a recent trend, and they are very promising. These algorithms include particle swarm optimization, simulated annealing, differential evolution, genetic algorithms, harmony search and many others.

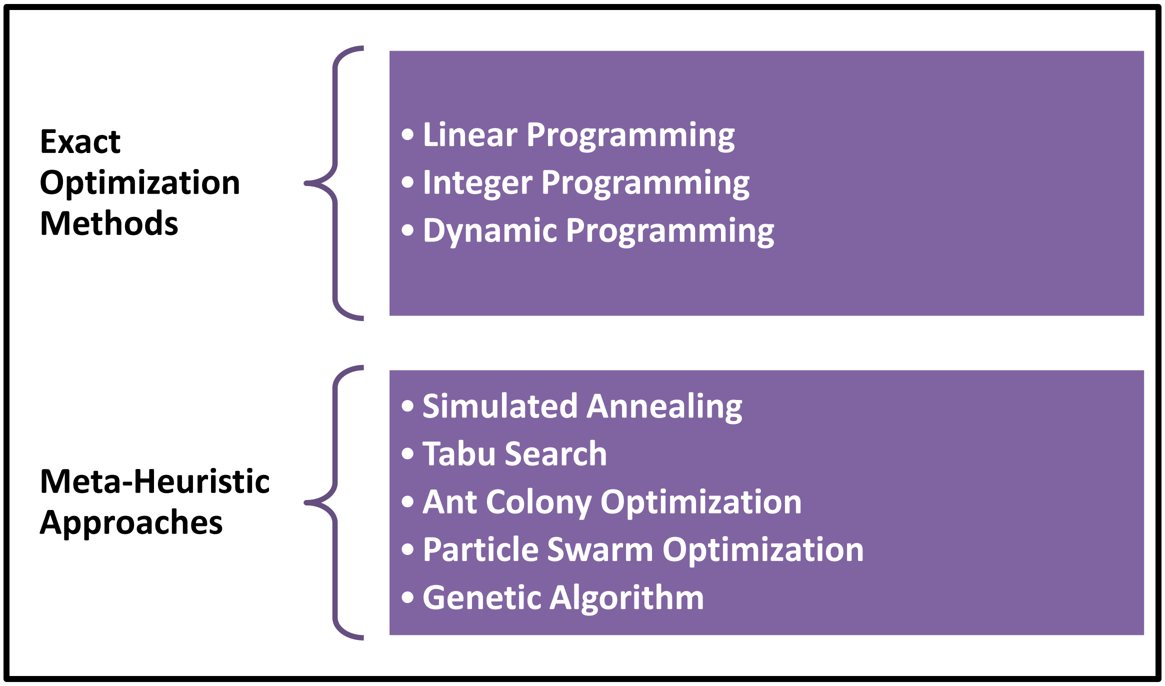

Figure 16: Various methods used to solve complex combinatorial optimization problems

4.3 Exact Optimization Methods:

Exact methods are guaranteed methods for finding an optimal solution and to prove its optimality for every instance of combinatorial optimization problems. The run-time, however, often increases exponentially with the instance size, and often only small or moderately-sized instances can be practically solved to provable optimality. Some of the exact optimization methods are explained in brief in the following sections.

4.3.1 Linear Programming:

Linear Programming is one of the most used optimization techniques of operations research [Zoints, S. 1974]. A linear programming problem may be defined as the problem of maximizing or minimizing a linear function subject to linear constraints. The constraints may be equalities or inequalities. Thus, Linear Programming (LP) is the process of taking various linear inequalities relating to some situation, and finding the "best" value obtainable under those conditions. It

derives its name from the fact that the LP problem is an optimization problem in which the objective functions and all the constraints are linear. A typical example would be taking the limitations of materials and labor, and then determining the "best" production levels for maximal profits under those conditions. This field of study is used every day in the organization and allocation of resources. It is also most extensively used in the areas of business and economics. These systems can have dozens or hundreds of variables, or more. Hence LP is a very important technique in the area of optimization.

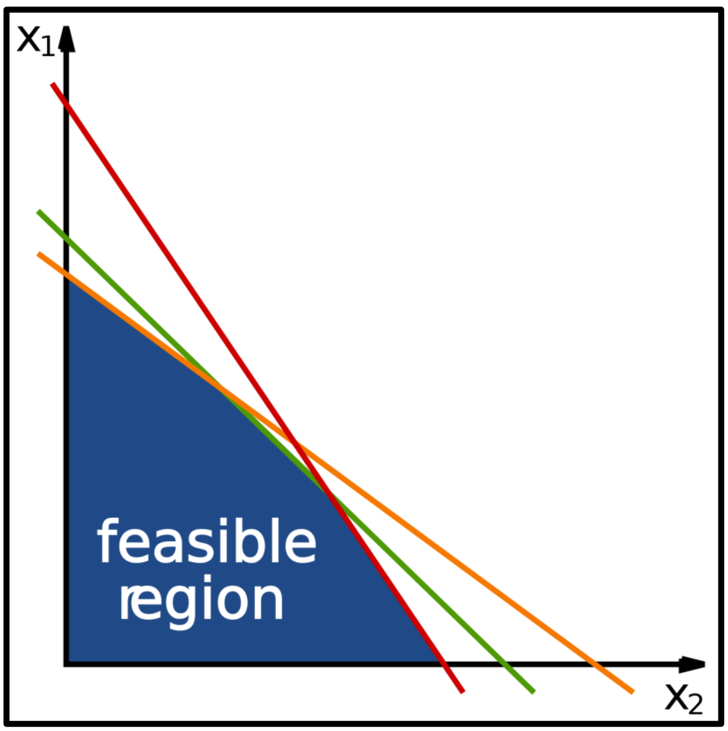

Figure 17: An example of a LP problem showing the bounded region on the graph

In general the LP problems are solved graphically by plotting the inequalities called the „constraints' to form a bounded area on the *x*,*y*-plane called the „feasibility region' as shown in the Figure 17. And then figuring out the coordinates of the corners of this feasibility region i.e. to find the intersection points of the various pairs of lines, and test these corner points in the formula called the "optimization equation" for which we are trying to find the minimum or

maximum value. However, not all LP problems can be solved graphically. As the number of variables and constraints increases the problem becomes complex thus requiring other methods like simplex method and dual simplex method. Some variables may be constrained to be nonnegative and others unconstrained. Some of the main constraints may be equalities and others inequalities. However, two classes of problems, called here the standard maximum problem and the standard minimum problem, play a special role. In these problems, all variables are constrained to be nonnegative, and all main constraints are inequalities.

The standard form of Linear Programming problem is given below:

Maximize: $\boldsymbol{CX}$ (the linear function to be maximized)

Subject to,

$\boldsymbol{AX} = \boldsymbol{b}$ (the constraints),

where,

$\boldsymbol{X} \geq \mathbf{0}$ (the non-negativity conditions)

$\boldsymbol{b} \geq \mathbf{0}$

The features of the standard form are:

- The objective is one of maximization.
- The constraints are all equations.
- The decision variables must be non-negative.
- The constant, b_j, in each constraint is non-negative.
- If the objective is one of minimization, the objective function Z is multiplied by -1.

4.3.2 Integer programming:

An integer programming (IP) problem is a mathematical optimization program in which some or all of the unknown variables are restricted to be integers. If only some of the unknown variables are required to be integers, then the problem is called a mixed integer programming problem. Finding an optimal solution to combinatorial optimization problems can be a difficult task. The difficulty arises from the fact that unlike linear programming, the feasible region of the combinatorial problem is not a convex set. Hence there is always a need to search a lattice of feasible points, or in the case of the mixed integer case, a set of disjoint half-lines or line segments to find an optimal solution.

In linear programming, due to the convexity of the problem, we can exploit that fact that any local solution is a global optimum. However, in integer programming, problems have many local optima and finding a global optimum to the problem requires one to prove that a particular solution dominates all rest of the feasible points. The general integer programming problem can be stated as shown below,

---

Maximize: $\boldsymbol{f}\,(\mathbf{X})$

Subject to,

$$\boldsymbol{g_j}\,(\mathbf{X}) = \mathbf{0}, \qquad j = 1, 2, \ldots, m,$$

$$\boldsymbol{h_i}\,(\mathbf{X}) \leq \mathbf{0}, \qquad i = 1, 2, \ldots, k,$$

$$\mathbf{X} = (x_1, x_2, \ldots, x_q, x_{q+1}, \ldots, x_n),$$

where, $x_1, x_2, \ldots, x_q$ are integers for a given q.

Assuming that f and h_i's are linear, and not considering g_j's, and considering all the variables in **X** to be non-negative. Then the formulation can be expressed in matrix form as,

Maximize: $\mathbf{CX}$

Subject to,

$$\mathbf{AX} \leq \mathbf{b}$$

$$\mathbf{X} \geq \mathbf{0} \qquad x_1, x_2 \ldots x_q \text{ are integers,}$$

where, $\mathbf{X} = (x_1, x_2, \ldots, x_q, x_{q+1}, \ldots., x_n)^T$,

C is a 1 x n real vector,

b is an m x 1 real vector,

A is an m x n real matrix.

In the above formulation,

- If $q=n$, then the problem is termed as an all-integer programming problem.
- If $1< q < n$, then the problem is termed as a mixed-integer programming problem.
- And if x_i = 0 or 1, where i = 1, 2… n, then the problem is called zero-one integer programming problem.

Whereas the simplex method is effective for solving linear programs, there is no single technique for solving integer programs. Instead, a number of procedures have been developed by many researchers in the past, and the performance of any particular technique in most cases is dependent on the type of the problem. Methods to date can be classified broadly as following one of three approaches:

a) Branch-and-Bound Enumeration,

b) Lagrangian Relaxation & Decomposition Methods

c) Cutting-plane techniques, and

d) Group-theoretic techniques.

4.3.3 Dynamic programming:

Dynamic programming (DP) is a very powerful algorithmic paradigm in which a problem is solved by identifying a collection of sub-problems and tackling them one by one, smallest first, using the answers to small problems to help figure out larger ones, until the whole lot of them is solved. Some of very easy real-world examples would be the investment of funds over a period of time and construction management projects. DP also uses the philosophy of implicit enumeration as does one of the integer programming approaches. Thus, DP refers to simplifying a complicated problem by breaking it down into simpler sub-problems in a recursive manner. While some decision problems cannot be taken apart this way, decisions that span several points in time do often break apart recursively; Bellman called this as the "Principle of Optimality". Bellman states that „An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision'. On the other hand if sub-problems can be nested recursively inside larger problems, so that dynamic programming methods are applicable, then there is a relation between the value of the larger problem and the values of the sub-problems. Bellman showed that a dynamic optimization problem in discrete time can be stated in a recursive, step-by-step form by writing down the relationship between the value function in one period and the value function in the next period. The relationship between these two value functions is called the Bellman equation. A Bellman equation also known as a dynamic programming equation is a necessary condition for optimality associated with the mathematical optimization method of DP. It writes the value of a decision problem at a certain point in time in terms of the payoff from some initial choices and the value of the remaining

decision problem those results from those initial choices thus breaking a dynamic optimization problem into simpler sub-problems, as Bellman's Principle of Optimality prescribes.

Literature is in abundance when it comes to application of DP to solve various optimization and scheduling problems. In the past Bellman (1955) introduced a DP formulation to solve the finite horizon equipment replacement problem with general costs considering single challenger in each decision period. Recently Espiritu *et al.,* (2008) have used an iteratively combined DP and Integer Programming (IP) approach to obtain cost-efficient system-level component replacement schedules. The main objective in this problem was to minimize the total net present value of unmet demand along with the consideration of system availability, maintenance, and purchase costs over a finite planning horizon. This model was applied to solve capital replacement problems for a set of heterogeneous assets within electricity transmission and distribution systems grid subject to annual budget constraints. In this model DP algorithm is developed and applied to the system components individually to obtain the optimal replacement policy for each asset in the system. These solution obtained from DP is fed as input for IP1 to check if the budget has been violated or not. If the budget is violated then the IP2 is used to determine the recommended replacement schedule with the minimum net present value of the total system replacement cost. Dynamic programming (DP), due to the following properties, suits best the maintenance scheduling problems [Yamayee *et al.,* 1983]: (1) It is especially suitable for optimization problems where a sequence of decisions is involved (2) The objective function to be used in DP does not need to be a continuous function of decision and state variables; and (3) Neither analytic forms for the objective function or constraint functions are not required to be represented in analytic forms, provided these function values can be obtained by other means when required.

4.4 Meta-Heuristics Approaches:

Heuristic is defined as an algorithm that usually, but not always, works or that gives nearly the right answer [Black, 2004]. An algorithm for a problem is a scientific procedure which will converge to the best feasible solution to the problem. Analysts in industries, businesses and research areas are often faced with problems of such complexity that the standard algorithms are not capable of solving those problems. There are several reasons which make the problem hard combinatorial problem;

- The dimensions of the problem may be so large that the application of the fastest-known algorithm on the fastest computer may take a prohibitive amount of computational time. This is certainly true for certain vehicle routing problems and travelling salesman problems.
- The problem may be virtually impossible to formulate in explicit terms. And in most of the cases it may be difficult to express many features of the problem in quantitative terms.
- Data collection may be beset with problems of accuracy and magnitude. For example, in large-scale location problems the analyst may be faced with calculating an enormous number of location-to-location distances. In order to provide this information in reasonable time it may be necessary to make approximations. But most often the use of approximate data makes the concept of an optimal solution meaningless.

Due to the shortcomings of the exact methods and heuristics, the possibility of applying metaheuristics for solving the component replacement problems in various areas has intrigued researchers from past many years. And also due to the generality of the concept of

metaheuristics, it is hardly possible to give a precise definition of what metaheuristics exactly is. Following are some of the definitions quoted in the literature.

"A metaheuristic refers to a master strategy that guides and modifies other heuristics to produce solutions beyond those that are normally generated in a quest for local optimality." [Goldberg, 1989]

"A metaheuristic is a general algorithmic framework which can be applied to different optimization problems with relatively few modifications to make them adapted to a specific problem." [Dorigo *et al*., 1996]

"Metaheuristic can also be defined as a high-level algorithmic framework or approach that can be specialized to solve optimization problems." [Black, 2009]

Metaheuristics are typically high-level strategies which guide an underlying, more problem specific heuristic, to increase their performance. The main goal is to avoid the disadvantages of iterative improvement and, in particular, multiple descents by allowing the local search to escape from local minima. This is achieved by either allowing worsening moves or generating new starting solutions for the local search in a more intelligent way than just providing random initial solutions. Many of the methods can be interpreted as introducing a bias such that high quality solutions are produced quickly. This bias can be of various forms and can be cast as descent bias (based on the objective function), memory bias (based on previously made decisions) or experience bias (based on prior performance). Many of the metaheuristic approaches rely on probabilistic decisions made during the search. But, the main difference to pure random search is that in metaheuristic algorithms randomness is not used blindly but in an intelligent, biased form [Stützle, 1999]

Metaheuristics are used for combinatorial optimization in which an optimal solution is sought over a discrete search-space. Metaheuristics make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. In short metaheuristics can be characterized as high level strategies for exploring search spaces by using different methods. Metaheuristics can be categorized in different ways depending on the characteristics considered for differentiating them. For instance, „nature inspired' vs. „non-nature inspired' categorization traces the origin of metaheuristics, whereas the „memory usage' vs. „memory-less methods' categorization differentiates metaheuristics that use long term and short term memories. Further based on the search methods the metaheuristics can also be categorized as „single point' vs. 'population-based search' Blum *et al.,* (2008).

4.4.1 Tabu Search:

Tabu Search (TS), is a metaheuristic originally proposed by Glover in 1986, to address various combinatorial problems that have appeared in the operations research literature. TS can be superimposed on other procedures to prevent them from becoming trapped at locally optimal solutions. In most cases, the methods described provide solutions very close to optimality and are among the most effective, if not the best, to tackle the difficult problems at hand. These successes have made TS extremely popular among those interested in finding good solutions to the large combinatorial problems encountered in many practical settings.

Tabu Search is an iterative procedure which was first designed for finding the solutions of hard combinatorial optimization problems. And since then TS is been used to solve a wide range of hard optimization problems such as job shop scheduling, graph coloring (related), the Travelling Salesman Problem (TSP) and the capacitated arc routing problem. Current

applications of TS span the realms of resource planning, telecommunications, VLSI design, financial analysis, scheduling, space planning, energy distribution, molecular engineering, logistics, pattern classification, flexible manufacturing, waste management, mineral exploration, biomedical analysis, environmental conservation and scores of others. A distinguishing feature of TS is embodied in its exploitation of adaptive forms of memory, which equips it to penetrate complexities that often confound alternative approaches [Glover *et al.*, 1997]. A flowchart of TS algorithm is shown in Figure 18:

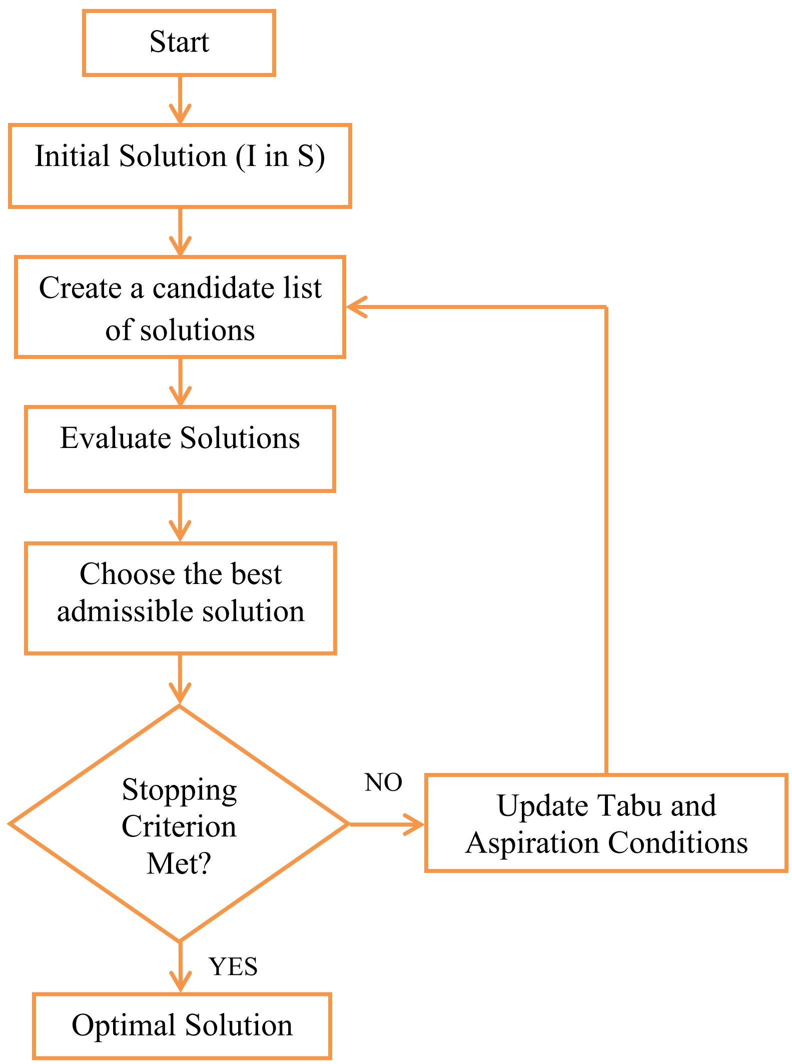

Figure 18: Tabu Search Algorithm Flowchart

Tabu search begins by initialization of a Tabu List. A local search is then used to scan the neighborhood, *N(s)*, and an initial trial solution, *s* is chosen randomly. Among the *k* neighbors of *s*, the best neighbor, *s^*, is selected to replace the current solution, *s*. Upon execution of a move, selected attributes of the move are stored in a Tabu List, and are declared „tabu active' for a predefined number of iterations. An example of a move attribute is the exchange of the cities at positions 4 and 5 in the case of a Travelling Salesman Problem (TSP). For the remainder of the TS run, a move to the best neighbor found at an iteration is banned if one or more of the attributes involved in the move are flagged as „tabu active' in the Tabu List. However, an aspiration criterion can be specified such that a prohibitive move can still be admissible if this criterion is satisfied. The iterative process of the memory enhanced local search is repeated until a termination criterion is met. The best solution found during a TS run is regarded as the optimal solution.

Apart from the definition of a neighborhood structure, as required for any simple local search algorithm, the following parameters need to be defined in the application of TS to a combinatorial optimization problem.

1) **Memory Structure:** Tabu values are stored in a short-term memory of the search called as the tabu list and usually only a fixed and fairly limited quantity of information is recorded. In any given context, there are several possibilities regarding the specific information that is recorded. One could record complete solutions, but this requires a lot of storage and makes it expensive to check whether a potential move is tabu or not; it is therefore seldom used. The most commonly used tabu values involve recording the last few transformations performed on the current solution and prohibiting reverse

transformations, others are based on key characteristics of the solutions themselves or of the moves.

2) **Aspiration Criterion:** While central to TS, tabu values are sometimes too powerful: they may prohibit attractive moves, even when there is no danger of cycling, or they may lead to an overall stagnation of the searching process. It is thus necessary to use algorithmic devices that will allow one to revoke (cancel) the tabu values. These are called aspiration criteria. The simplest and most commonly used aspiration criterion consists in allowing a move, even if it is tabu, if it results in a solution with an objective value better than that of the current best-known solution (since the new solution has obviously not been previously visited). The key rule in this respect is that if cycling cannot occur, tabu values can be disregarded.

3) **Termination Criterion:** The most commonly used stopping criteria in TS are:

- After a fixed number of iterations (or a fixed amount of CPU time);
- After some number of iterations without an improvement in the objective function value (this criterion is used most often);
- When the objective reaches a pre-specified threshold value.

In complex Tabu schemes, the search is usually stopped after completing a sequence of phases, the duration of each phase being determined by one of the above criteria.

4.4.2 Ant Colony Optimization:

Ant Colony Optimization (ACO) is a metaheuristic approach that was inspired by the foraging behavior of real ants. This algorithm is a member of ant colony algorithms family, and also a part

of swarm intelligence, and it constitutes some metaheuristic optimizations. Initially proposed by Marco Dorigo in 1992 in his PhD thesis, the first algorithm was aiming to search for an optimal path in a graph, based on the foraging behavior of ants seeking a path between their colony and a source of food. As described in his research, that ant's way of foraging enables them to find shortest paths between food sources and their nest. Initially, ants explore the area surrounding their nest in a random manner. As soon as an ant finds a source of food, it evaluates quantity and quality of the food and carries some of this food to the nest. During the return trip, the ant deposits a chemical pheromone trail on the ground. The quantity of pheromone deposited, which depends on the quantity and quality of the food, guides other ants to the food source. The indirect communication between the ants via the pheromone trials allows them to find shortest paths between their nest and source of food.

This functionality of real ant colonies id exploited in artificial ant colonies to help solve hard optimization problems. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behavior of ants. In general, the ACO approach is used in solving an optimization problem by iterating the following two steps:

- Solutions are constructed using a pheromone model, that is, a parametric probability distribution over the solution space.

- The constructed solutions and possibly solutions that were constructed in earlier iterations are used to modify the pheromone values in a way that is deemed to bias future sampling towards high quality solutions.

The ACO metaheuristic consists of an initialization step and a loop over three algorithmic components. A single iteration of the loop consists of constructing solutions by all ants, their (optional) improvement with the use of a local search algorithm, and an update of the pheromones. A basic ACO algorithm flowchart and pseudo code is shown in Figure 19.

Algorithm: Ant Colony Optimization Metaheuristic

Set parameters, initialize pheromone trials

While (termination condition not met) **do**

ConstructAntSolutions

ApplyLocalSearch {optional}

UpdatePheromones

end while

ConstructAntSolutions: A set of *m* artificial ants construct solutions from elements of a finite set of available solution components C = $\{c_{ij}\}$, i=1,…,n, j=1,….,D_i. A solution construction starts with an empty partial solution $s^p = \emptyset$. Then, at each construction step, the current partial solution s^p is extended by adding a feasible solution component from the set of feasible neighbors.

The choice of a solution component from $N(s^p)$ is done probabilistically at each construction step. The exact rules for the probabilistic choice of solution components vary across different ACO variants. The best known rule is the one of Ant System (AS):

$$p(c_{ij}|s^p)=\frac{\tau_{ij}^{\alpha}\ .\ \eta(c_{ij})^{\beta}}{\sum_{c_{ij}\ \epsilon\ N(s^p)}.\tau_{ij}^{\alpha}\ .\eta(c_{ij})^{\beta}}\ , \qquad \forall\ c_{ij} \in\ N(s^p),$$

where τ_{ij} is the pheromone value associated with the component c_{ij}, and $\eta(.)$ is a function that assigns at each construction step a heuristic value to each feasible solution component $c_{ij} \in N(s^p)$. The values that are given by this function are commonly called heuristic information. Furthermore, α and β are positive parameters, whose values determine the relative importance of pheromone versus heuristic information.

ApplyLocalSearch: Once solutions have been constructed, and before updating pheromones, often some optional actions may be required. These are often called *daemon actions*, and can be used to implement problem specific and/or centralized actions, which cannot be performed by single ants. The most used daemon action consists in the application of local search to the constructed solutions: the locally optimized solutions are then used to decide which pheromones to update.

UpdatePheromones: The aim of the pheromone update is to increase the pheromone values associated with good or promising solutions, and to decrease those that are associated with bad ones. Usually, this is achieved (i) by decreasing all the pheromone values through pheromone evaporation, and (ii) by increasing the pheromone levels associated with a chosen set of good solutions S_{upd}:

$$\tau_{ij} \leftarrow (1-\rho).\tau_{ij} + \rho. \sum_{s \epsilon S_{upd} \,|c_{ij} \epsilon s} F(s)\,,$$

where S_{upd} is the set of solutions that are used for the update, $\rho\ \epsilon$ (0; 1) is a parameter called evaporation rate, and F : S $\rightarrow R_o^+$ is a function such that f(s) < f(s') => F(s) ≥ F(s'), ∀s ≠ s' ϵ S. F(.) is commonly called the fitness function.

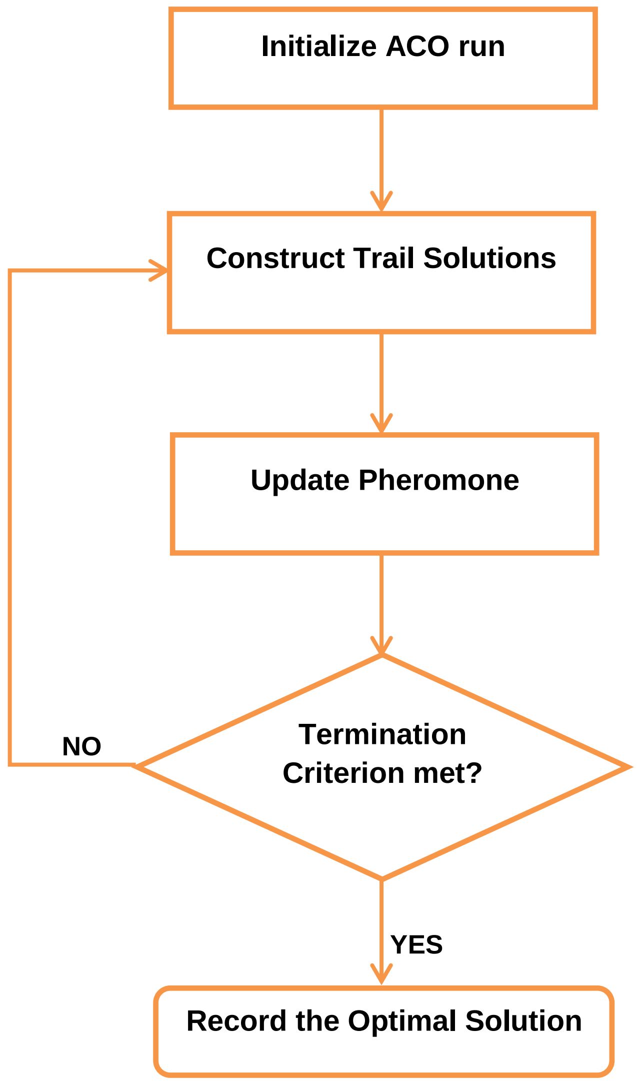

Figure 19: ACO Algorithm Flowchart

Algorithmic implementations of these methodologies have shown very promising result for the well-known Traveling Salesman Problem [Merkle *et al*., 2002] and have recently been applied to scheduling problems, as Job-Shop, Flow-Shop, Resource Constrained Project [Besten *et al*., 2000] and Single Machine Total Weighted Tardiness problems [Dorigo *et al.*, 1996]

4.4.3 Particle Swarm Optimization:

The Particle Swarm Optimization (PSO) algorithm was proposed by Dr. James Kennedy and Dr. Russell C. Eberhart in 1995, it is mainly motivated by social behavior of organisms such as bird flocking and fish schooling, mimics the collective intelligent behavior of “unintelligent” creatures. PSO is a part of Swarm Intelligence which deals with natural and artificial systems composed of many individuals that coordinate using decentralized control and self-organization.

The typical swarm intelligence system has the following properties:

- It is composed of many individuals;
- The individuals are relatively homogeneous (i.e., they are either all identical or they belong to a few typologies);
- The interactions among the individuals are based on simple behavioral rules that exploit only local information that the individuals exchange directly or via the environment (stigmergy);
- The overall behavior of the system results from the interactions of individuals with each other and with their environment, that is, the group behavior self-organizes.

The particle swarm optimization method is a population based method just as Genetic Algorithms (GA’s) but instead of fighting one against the other their concept is about mutual cooperation. It is important to mention, that PSO algorithm is not only a tool for optimization, and it is also a tool on behalf of socio-cognition of human and artificial cause, based on principles of social psychology [Kennedy *et al.,* 1995].

The principles of PSO algorithms are stated below:

- Proximity principle: the population should be able to carry out simple space and time computations.
- Quality principle: the population should be able to respond to quality factors in the environment.
- Diverse response principle: the population should not commit its activities along excessively narrow channels.
- Stability principle: the population should not change its mode of behavior every time the environment changes.
- Adaptability principle: the population must be able to change behavior mode when it's worth the computational price.

In PSO, each single solution is a "bird" in the search space which is referred to as a "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations, at every iteration each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called *gbest*. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called *lbest*.

Once the algorithm finds the best values for *pbest* and *gbest*, the update process for the velocity and position of each solution is performed applying the formula as given:

A) v[ ] = v[ ]+c1*rand()*(pbest[ ]-present[ ])+c2*rand()*(gbest[ ]-present[ ])

B) present [ ] = present[ ] + v[ ]

where,

v[] is the particle velocity

present [] is the current particle (solution)

rand () is a random number between (0,1)

c1, c2 are learning factors; usually c1 = c2 = 2

Particles' velocities on each dimension are clamped to a maximum velocity *Vmax*. If the sum of accelerations would cause the velocity on that dimension to exceed *Vmax*, which is a parameter specified by the user then the velocity on that dimension is limited to *Vmax*.

The PSO algorithm can be best described in general as follows:

1) For each particle, the position and velocity vectors will be randomly initialized with the same size as the problem dimension.
2) Measure the fitness of each particle (*pbest*) and store the particle with the best fitness (*gbest*) value.
3) Update velocity and position vectors according to (1) and (2) for each particle.
4) Repeat steps 2–3 until a termination criterion is satisfied.

One of the reasons that PSO is attractive is that there are very few parameters to adjust. PSO has been used across a wide range of applications, as well as for specific requirement. Generally speaking, PSO like any other evolutionary algorithms have been applied for system design,

multi-objective optimization, pattern recognition, biological system modeling, scheduling and planning, image segmentation and job shop scheduling.

The pseudo code of the procedure is as follows:

Algorithm: Particle Swarm Optimization

```
For each particle
   Initialize particle
End
Do
   For each particle
      Calculate fitness value
      If the fitness value is better than the best fitness value (pbest) in history
         set current value as the new pbest
   End
   Choose the particle with the best fitness value of all the particles as the gbest
   For each particle
      Calculate particle velocity according equation (A)
      Update particle position according equation (B)
   End
While maximum iterations or minimum error criteria is not attained
```

The flowchart of a basic PSO algorithm is as shown below:

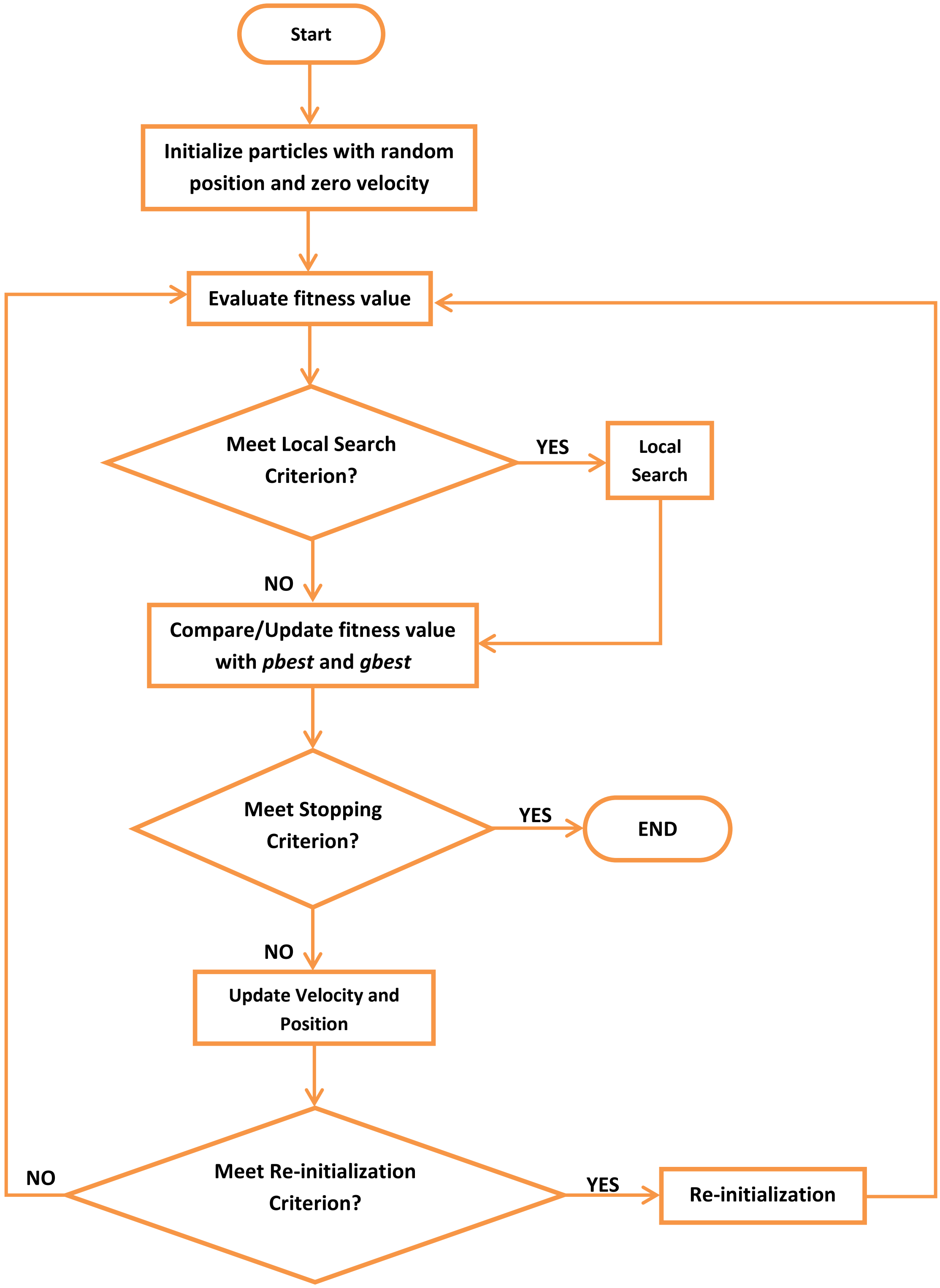

Figure 20: PSO Algorithm Flowchart

4.4.4 Genetic Algorithms:

Genetic Algorithms (GA's) are search algorithms based on the mechanics of natural selection and natural genetics. Invented and developed by John Holland and his colleagues in 1975 at the University of Michigan, GA's are based on the Darwin's theory of evolution thus GAs belongs to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural processes of the selection of individuals and the evolution of species as well as reproduction mechanisms and the genetic transmission of characteristics. As a result of natural mechanisms new species are originated ousting those that are not adjusted to their environment as well as themselves. In terms of searching behaviour, simple GA's fall under the category of global optimization methods, as trial solutions of a GA run are generated based on global information accrued throughout the search process. According to Goldberg, (1989) compared to any other traditional procedures the GA's are different in following four ways:

- GA's work with a coding of the parameter set, not the parameters themselves.
- GA's search from a population of points, not a single point.
- GA's use payoff (objective function) information. Not derivatives or other auxiliary knowledge.
- GA's use probabilistic transition rules, not deterministic rules.

To use GA's for any optimization purposes first and most important part is to understand the representation of the GA and its operators for encoding potential solutions. In Figure 19 the difference between chromosome, gene and allele is illustrated.

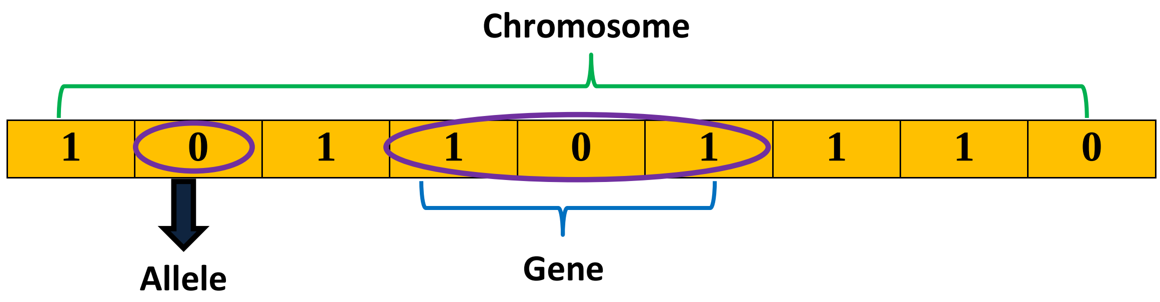

Figure 21: Alleles, Genes, & Chromosomes

A chromosome describes a string of certain length where all the genetic information of an individual is stored. In GA's, a chromosome (also sometimes called a genome) is a set of parameters which define a proposed solution to the problem that the genetic algorithm is trying to solve. Although nature often uses more than one chromosome, most GA applications use only one chromosome for encoding the genotypic information. Each chromosome consists of many alleles. Alleles are the smallest information unit in a chromosome and in GA's most often an allele is represented using only one data type. Like in the above example we used binary encoding so in this case an allele could be either the value 1 or 0. And a group of alleles form a gene which is responsible for specific phenotypic property.

The aim of a GA is to improve in a constant way the adjustment function value until a global extremum is reached by that function. In order to construct a GA it is indispensable to define its five component elements:

- A genetic representation of solutions to a given problem
- A method of a generating an initial population of solutions
- A fitness function form (the evaluation of potential solutions)

- Defining and selecting those genetic operators that modify genes in chromosomes, and
- Values of the GA control parameters (e.g. the population size or the probability of employing a given operator)

Types of Encoding: When adopting GAs for combinatorial optimization problems, trial solutions to the problem are represented by strings of chromosomes, in which the solution parameters are encoded and stored. Thus encoding of chromosomes is one main criterion before starting to solve problem with GA. There are different types of encoding is possible but mostly the type of encoding used to solve a particular problem depends on the nature of the problem. Some of encoding types are explained as below:

a) **Binary Encoding:** Binary encoding is the most common type of representation used in GAs to solve many optimization problems. In binary encoding every chromosome is represented by string consisting of bits 0 or 1 as shown in Figure 22:

Chromosome A	**1**	**0**	**0**	**1**	**1**	**1**	**0**	**1**	**0**
Chromosome B	**0**	**0**	**1**	**1**	**0**	**1**	**1**	**1**	**0**

Figure 22: Example of chromosomes with binary encoding

Binary encoding gives many possible chromosomes even with a small number of alleles. For many combinatorial optimization problems this type of representation allows a direct and very natural encoding.

b) **Integer or Permutation Encoding:** Permutation encoding can be used in ordering problems, such as travelling salesman problem or task ordering problem. In permutation

encoding, every chromosome is a string of numbers, which represents number in a sequence.

Chromosome A	**5**	**3**	**1**	**6**	**8**	**2**	**9**	**4**	**7**
Chromosome B	**8**	**6**	**9**	**3**	**5**	**4**	**1**	**7**	**2**

Figure 23: Example of chromosomes with integer encoding

Integer or permutation encoding is best used for combinatorial optimization problems. Since the essence of combinatorial optimization problems is the search for a best permutation or combination of items subject to constraints, integer or permutation encoding can be the best way for these types of problems.

c) Real-valued Encoding: Real-valued encoding can be used in problems, where some complicated values, such as real numbers, are used. Use of binary encoding for this type of problems would be very difficult. In real-value encoding, every chromosome is a string of some values. Values can be anything connected to problem, form numbers, real numbers or chars to some complicated objects.

Chromosome A	**5.3**	**3.1**	**6.1**	**2.6**	**3.83**	**0.32**	**10.9**	**8.547**	**1.007**
Chromosome B	**A**	**H**	**T**	**U**	**K**	**D**	**A**	**X**	**G**
Chromosome C	**Right**	**Center**	**Left**	**Back**	**Front**	**Center**	**Back**	**Right**	**Left**

Figure 24: Example of chromosomes with real-value encoding

Real-valued encoding is best used for function optimization problems. However real-valued representations cannot exclusively be used for encoding real-valued problems, but also for other permutation and combinatorial problems. Trees, schedules, tours, or other combinatorial problems can easily be represented by using real-valued vectors.

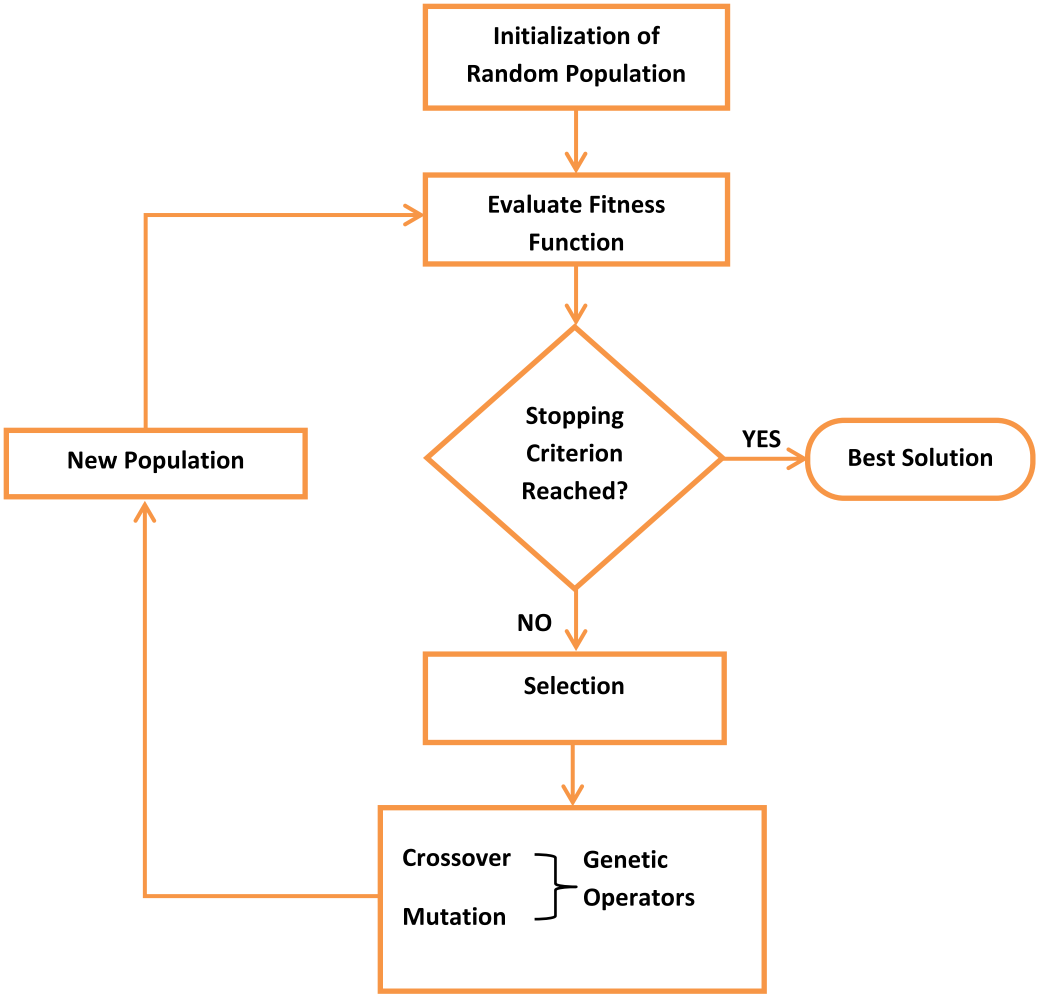

Figure 25: Flowchart of Genetic Algorithm

As shown in Figure 26, a simple genetic algorithm that yields good results in many practical problems is composed of following steps:

1. **Initialization of random population:**

   Initially many individual solutions are randomly generated to form an initial random population. Each population representation is a potential solution. The size of the population depends on the nature of the problem, but typically it contains several hundreds or thousands

of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the search space).

2. **Fitness Function:**

   In GA's, whether or not a chromosome is selected for reproduction depends on its fitness function. Therefore, a fitness function that evaluates the quality of individual chromosome must be specified beforehand.

3. **Selection:**

   GA selection operators perform the equivalent role to natural selection. The overall effect is to bias the gene set in following generations to those genes which belong to the most fit individuals in the current generation. In order for the population of chromosomes to evolve towards better solutions, parent trial solutions are stochastically chosen based on relative fitness, from the current initial population for the reproduction of offspring. Although trial solutions of higher fitness should be chosen by higher probability, selection pressure should not be too high to avoid premature convergence.

   There are numerous selection schemes described in the literature; "Roulette wheel" selection, Tournament selection, Rank selection, Random selection, Steady state selection, Elitism. These, in essence, mimic the processes involved in natural selection.

   a) **Roulette Wheel Selection:** Roulette wheel selection is a genetic operator used in GAs for selecting potentially useful solutions for recombination or reproduction of new offspring's. Parents are selected according to their fitness. The better the chromosomes are, the more chances to be selected they have. Imagine a roulette wheel where all chromosomes in the population are placed, every chromosome has its probability of getting selected accordingly to its fitness function, as shown:

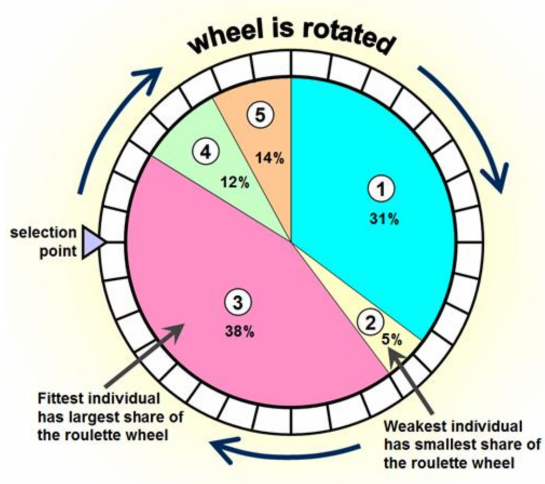

Figure 26: Example of Roulette-Wheel Selection

b) **Tournament Selection:** Tournament selection involves running several "Tournaments" among a few individuals chosen at random from the initial population. The winner of each tournament (the one with the best fitness) is selected for crossover. Selection pressure is easily adjusted by changing the tournament size. If the tournament size is larger, weak individuals have a smaller chance to be selected.

c) **Rank Selection:** The limitation of roulette-wheel selection is that, when the fitness values of any individual differs to a large extent. For example, if the best chromosome fitness is 90% of the entire roulette wheel then the other chromosomes will have very few chances to be selected. However, this can be avoided using Rank selection method to select the fittest chromosomes for reproduction.

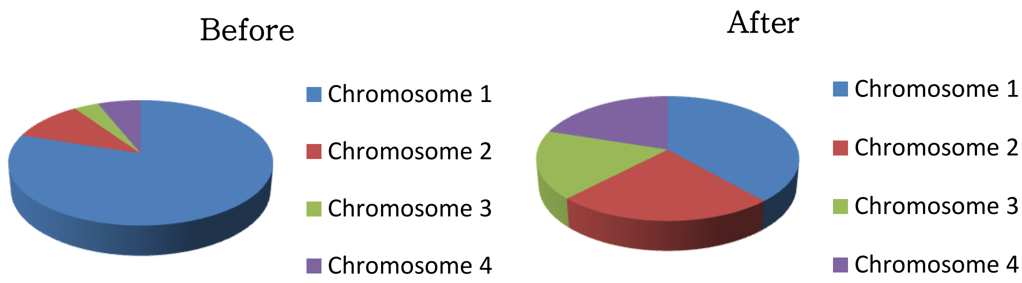

Figure 27: Example of Rank Selection

As shown in Figure 27 in this selection it first ranks the population and then every chromosome receives fitness from this ranking. For instance, the chromosome with the least fitness values will have fitness rank 1; the second least fitness value chromosome will have fitness rank 2, and so on. And finally the chromosome with most fitness value will have fitness rank N (where N = number of chromosomes in population). After this ranking system all the chromosomes will have a chance to be selected for next population. However, this method can lead to slower convergence, because the best chromosomes do not differ so much from one another.

d) Elitism: Elitism is the process of selecting the better individuals, or more to the point, selecting individual with a bias towards the better ones. According to this selection it first copies the best chromosome (or a few best chromosomes) to new population and rest of the procedure is done in classical way. Elitism is important since it allows the solution to get better over time and thus rapidly increases the performance of GA, because it prevents losing the best found solution.

4. **Genetic Operators:**

In an attempt to explore the decision space of an optimization problem, GA's operate on a population of trial solutions by iteratively modifying the components of chromosomes contained in the population. In particular, a number of chromosomes are selected to produce offspring chromosomes, which undergo a series of genetic operations, generally known as recombination operations.

- **Crossover:** Crossover operation is analogous to the biological reproduction. In GA's the crossover is performed by exchanging the elements of two parent chromosomes to produce two new offspring chromosomes governed by a crossover probability. The objective of performing crossover is to obtain a better chromosome by exploiting partial information contained in two relatively good parent chromosomes. There are different types of crossover methods available. Some of the most popular ones are listed below:
    - **One Point Crossover:** A random crossover point is selected within a chromosome and the genes are interchanges between the two parents beyond this crossover point. Hence two new offspring's are produced as shown in the example below:

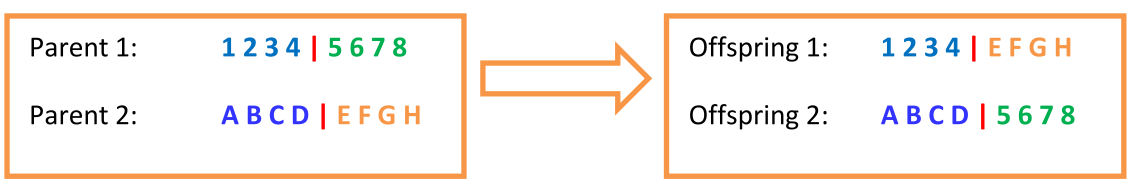

Figure 28: One Point Crossover

    - **Two Point Crossover:** A crossover operator randomly selects two crossover points within a chromosome then interchanges the two parent chromosomes between these points to produce two new offspring's as shown below:

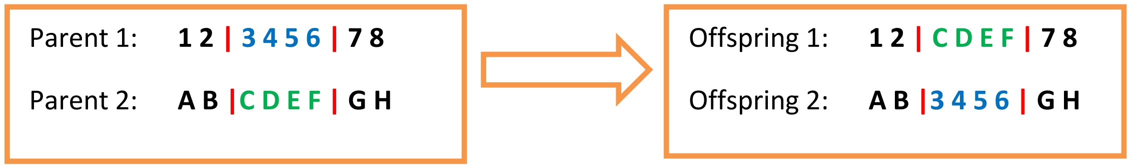

Figure 29: Two Point Crossover

- **Mutation:** Mutation is a genetic operator that alters one or more gene values in a chromosome from its initial state. This can result in entirely new gene values being added to the gene pool. With these new gene values, the genetic algorithm may be able to arrive at better solution than was previously possible. Mutation is an important part of the genetic search as it helps to prevent the population from stagnating at any local optima. It is governed by the user-definable mutation probability. This probability is usually set as low as 1%. A typical mutation operation is as shown in the example below:

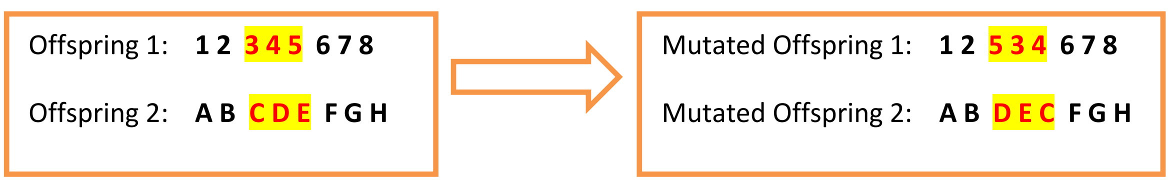

Figure 30: Mutation Operation

5. **Reproduction/New Population:** Recombined chromosomes and parent chromosomes of the current generation are combined to form the next generation using the operations described above. Normally, the best chromosomes are identified in the current generation are retained. More importantly, sufficient diversity should be maintained in any new generation to increase the likelihood of finding the global optimum.

6. **Termination Criterion:** A GA run is stopped when a prescribed maximum number of generations have been reached. Alternatively, termination criteria such as stagnation of the best found objective function value (cost) can be adopted.

It can be seen that in order to implement GAs, a number of parameters are required to be defined in advance, including the size of the population, a crossover probability, a mutation probability, a selection method, a population updating method and also a termination criterion.

Conclusion:

In this present chapter different methods of optimization techniques were introduced and reviewed. And different types of optimization methods along with various heuristic and meta-heuristic approaches are explained in detail. A very important topic of evolutionary algorithms such as ACO, PSO and GAs were introduced and presented to understand its working, formulation and methodology which will help us formulate the objective function and also evaluate the fitness function of the problem in this research.

Chapter 5

CONSTRAINT HANDLING METHODS

5.1 Introduction:

In the previous chapter various optimization techniques were introduced emphasizing more on the evolutionary algorithms. In this chapter, a general introduction to constraint handling techniques and penalty functions used in evolutionary algorithms are presented. The main objective of this chapter is to categorize various penalty functions and to understand the use of those penalty functions in solving constrained optimization problems. The main types of penalty function – static, dynamic, and adaptive – are described in brief. And in the later part the Death Penalty functions are introduced which will be used in solving the component replacement problem of the power distribution system subject to budget constraints, using genetic algorithms.

5.2 Constraints Handling in the Optimization Problems:

In general, an optimization problem can be divided into two types, a single objective optimization and multi-objective optimization problem. The single objective optimization problem aims to find a single solution to the objective function which reflects the best solution from a set of solutions; whereas multi- objective problems aims to find a set of non- dominated solutions which is close to Pareto Optimal Set. Virtually all situations (or conditions) which are intended towards making a logical decision involve some or the other forms of constraints.

However, various forms of these constraints distinguish the various types of optimization problems. Depending on the visualization of the problem under consideration, these constraints can arise as rules, data dependencies, algebraic expressions or some other forms Dhar & Ranganathan, (1990). Hence constrained optimization problems have been extensively studied in

field of operations research. In these problem formulations usually the constraints are quantitative, and the solver (such as GA) optimizes (maximizes or minimizes) the value of a specified objective function subject to the constraints. In discrete domains, most of the problems for instance, the knapsack problem, set covering problem, vehicle routing problem, and all types of scheduling and timetabling problems are all combinatorial optimization with constraints. To handle these constraints in an optimization problem, some of the constraint handling techniques were introduced and are designed to solve these constrained optimization problems.

5.3 Constraint Handling in Genetic Algorithms:

There are several approaches proposed in GAs to handle constrained optimization problems. To handle constraints, different methods have been proposed in the past and they can be classified into two groups: (i) generic methods that do not exploit the mathematical structure of the constraint, and (ii) specific methods that are only applicable to a special type of constraints. A constrained optimization problem is usually written as a nonlinear optimization problem of the following form:

Optimize $f(x)$ $\quad x = (x_1, \ldots, x_n) \in R^n$

subject to,

$g_i(x) \leq 0$ $\quad$ for $i = 1, \ldots, q$ $\quad$ (Inequality constraints)

$h_i(x) = 0$ $\quad$ for $i = q + 1, \ldots, m$ $\quad$ (Equality constraints)

where,

$x \in F \subseteq S$. The set $S \subseteq R^n$ defines the search space and the set $F \subseteq S$ defines a feasible search space. The search space S is defined as an n-dimensional rectangle in R^n whereas the feasible set F is defined by an intersection of S. There are q inequality and m-q equality constraints. Objective function and constraints can be linear or non-linear in the problem.

Generally, constrained optimization problems are difficult to solve. Due to the presence of constraints, the feasible space might be reduced to some portion of the total search space, and finding feasible solutions itself could be a daunting challenge. One of the major issues of constrained optimization is how to deal with the infeasible individuals throughout the search process. One way to handle infeasible individuals is to completely disregard them and continue the search process with feasible individuals only.

There are several approaches proposed in GA's to handle constrained optimization problems. These approaches can be grouped in four major categories as shown in Figure 30 Michalewicz & Schouenauer, (1996):

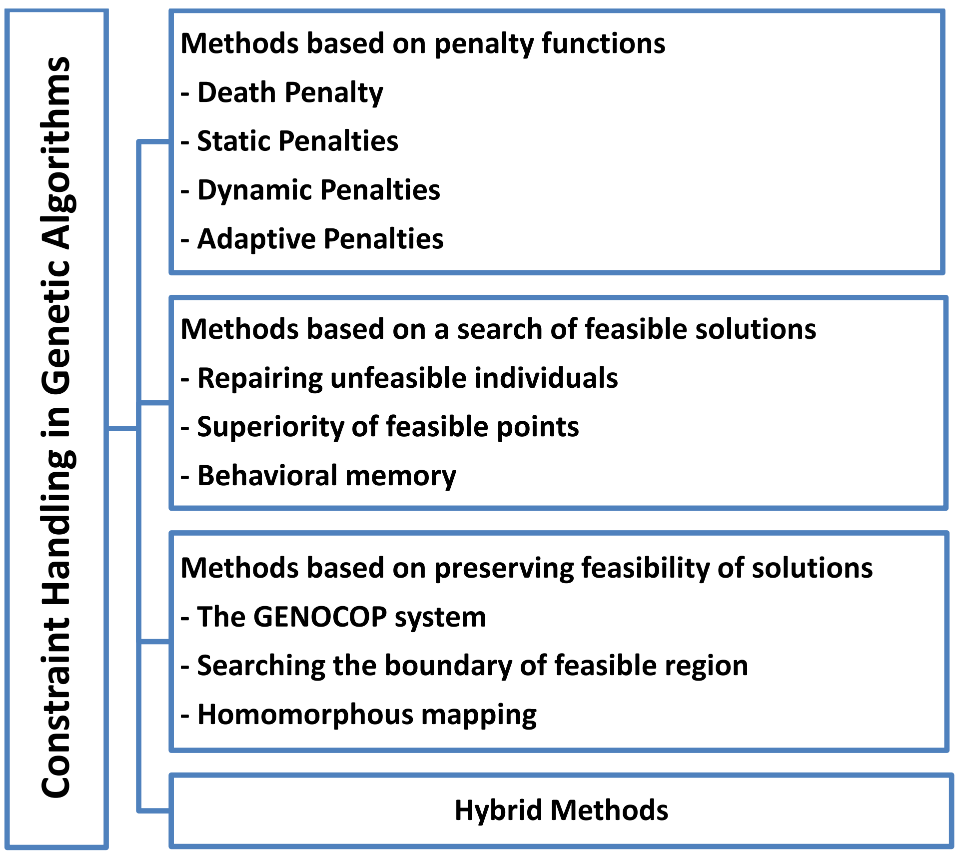

Figure 31: Different approaches to handle constrained optimization using GA's

Most of the problems in the fields (that are stated above) are classified as constrained optimization problems. Since GA's are directly applicable only to unconstrained optimization, it is necessary to use some additional methods that will keep solutions in the feasible region. The most popular approach in GA community to handle constraints is to use penalty functions that penalize infeasible solutions by reducing their fitness values in proportion to their degrees of constraint violation. In the present research work, we analyze these penalty-based methods to penalize the constraint violations in the component replacement schedules of power distribution systems.

5.4 Penalty Functions:

Penalty functions are by far the simplest and the most commonly used methods for handling constraints using GA's [Tessema & Yen, 2006]. The main idea of penalty functions is to transform a constrained optimization problem into an unconstrained one by adding (or subtracting) a certain value to/from the objective function based on the amount of constraint violation present in a certain solution [Fiacco & McCormick, 1968]. This constrained handling technique is known as the penalty function method. The most common approach in the evolutionary algorithms community to handle constraints (particularly, inequality constraints) is to use penalties. Penalty functions were originally proposed by Richard Courant in the 1940s and were later expanded by Carroll, Fiacco & McCormick [Coello *et al,*. 2002].

In mathematical programming, two kinds of penalty functions are considered: exterior and interior. In the case of exterior methods, it penalizes infeasible solutions by moving the solutions in the infeasible region towards the feasible region. In the case of interior methods, the penalty term is chosen such that its value is small at points away from the constraint boundaries and which tends to infinity as the constraint boundaries are approached. Then, by penalizing the

feasible solutions, the subsequent points generated will always lie within the feasible region since the constraint boundaries act as barriers during the optimization process. The main idea of interior penalty functions is that an optimal solution requires that a constraint be tight so that this optimal solution lies on the boundary between feasibility and infeasibility. Knowing this, a penalty is applied to feasible solutions when the constraint is not active; such solutions are called interior solutions. For a single constraint, this approach is straightforward however for multiple constraints; the implementation of interior penalty functions tends to be more complex.

Penalty functions method transforms constrained problem into unconstrained problem in two ways. The first method is to use additive form as follows:

$$eval(x) = \begin{cases} f(x), & if\ x \epsilon F \\ f(x) + p(x), & otherwise \end{cases}$$

where $p(x)$ presents a penalty term. If no violation occurs then $p(x) = 0$ and positive otherwise

Under this conversion, the overall objective function will be to $eval(x)$ which serves as an evaluation function in GAs.

The second method of penalizing the function is to use multiplicative form,

$$eval(x) = \begin{cases} f(x), & if\ x \epsilon F \\ f(x).p(x), & otherwise \end{cases}$$

For minimization problems, if no violation occurs $p(x) = 1$ and $p(x) > 1$ otherwise.

The additive penalty function type has received much more attention than the multiplicative penalty function type in the GA community [Özgür, 2005].

5.4.1 Static Penalty Functions:

A simple method to penalize infeasible solutions is to apply a constant penalty to those solutions which violate feasibility in any way. In this approach the penalties grow heavier with the increase in constraint violations. Thus for a minimization problem, the penalized objective function will be the un-penalized objective function plus a penalty parameter. And in the case of multiple constraints violations, metric value is added for each number of constraints that's been violated. As formulated in [Smith & Coit, 1997], for a minimization problem, the penalty function for a problem with m constraints is shown as below:

$$f_p(x) = f(x) + \sum_{i=1}^{m} C_i \delta_i \qquad \text{where} \begin{cases} \delta_i = 1, & \text{if constraint } i \text{ is violated} \\ \delta_i = 0, & \text{if constraint } i \text{ is violated} \end{cases}$$

where, $f_p(x)$ is the penalized objective function and $f(x)$ is the un-penalized function.

Another penalty method is the one which includes a distance metric for each constraint, and adds a penalty that becomes more severe with distance from feasibility. This approach takes into account the distance metric which provides the information regarding the nearness of the solution to feasibility which is relevant in the same magnitude to the fitness of the solution. As defined by [Smith & Coit, 1997], the general formulation for minimization problem is shown as below:

$$f_p(x) = f(x) + \sum_{i=1}^{m} C_i d_i^k \qquad \text{where } d_i = \begin{cases} \delta_i g_i(x), & \text{for } i = 1, \dots, q \\ |h_i(x)|, & \text{for } i = q+1, \dots, m \end{cases}$$

where d_i is the distance metric of the constant *i* applied to the solution *x* and the user defined parameter (*k* = 1 or 2).

The main drawback of this approach is that huge number of penalty coefficients has to be defined and there is no heuristic to determine these coefficients. For *m* constraints, this approach requires $m(2l+1)$ parameters in total. So, if we have, for example, six constraints and two levels, we would need 30 parameters, that's a very high number considering the small size of the proposed problem. Also, this method requires prior knowledge of the degree of constraint violation present in a problem (to define the levels of violation), which might not be always given (or easy to obtain) in real-world applications.

5.4.2 Dynamic Penalty Functions:

Unlike in static penalty functions where, the penalties added do not depend on the current generation number and remain constant during the entire evolutionary process, in dynamic penalty functions, the current generation number is involved in determining the value of the penalties Tessema & Yen, (2006). As stated earlier, the main disadvantage with the static penalty functions is the inability of the user to determine criteria for the *Ci* coefficients. And also, there are conflicting objectives involved with allowing exploration of the infeasible region, yet still requiring that the final solution to be feasible. Hence incorporating a dynamic aspect of the distance based penalty functions, improves the severity of the penalty for a given distance as the search progresses. This has the property of allowing highly infeasible solutions early in the search, while continually increasing the penalty imposed to eventually move the final solution to the feasible region. As defined in Smith & Coit, (1997), for a minimization problem a general form of a distance based penalty method incorporating a dynamic aspect based on length of search *t* is as shown below:

$$f_p(x,t) = f(x) + \sum_{i=1}^{m} s_i(t) d_i^k$$

where $s_i(t)$ is a monotonically non-decreasing in value with t. The t value gives the number of generations or number of solutions searched.

The primary objective of the dynamic penalty function formulations is to derive feasible solutions at the end of evolution. However, for this method to give optimal solution in the end of the evolution, the value of $s_i(t)$ needs to be adjusted appropriately, if $s_i(t)$ is too tolerant, then the final search may result in infeasible solutions, and on the other hand, if $s_i(t)$ is too severe, the search may converge to non-optimal feasible solutions. Hence for these penalty functions to perform well problem specific tuning of some of these parameters is inevitable. The dynamic penalty function proposed by [Joines & Houck, 1994] can be described as follows:

$$f_p(x,t) = f(x) + \sum_{i=1}^{m} (C_i t)^{\alpha} d_i^k,$$

where C and α are constants. This dynamic method increases the penalty as generation grows. The quality of a possible solution is very sensitive to changes of α and C values. There is no explanation about the sensitivity of the method for different values of C. However a reasonable choice for these parameters would be C=0.5, α=2.

Although most of the penalty functions are very simple and easy to implement, they often require several parameters to be chosen heuristically by users. These parameters are problem dependent and need prior knowledge of the degree of constraint violation present in a problem. Therefore, tuning the parameters leads to unnecessary computation for simple problems. Although dynamic penalty functions work better than static penalty functions, the main disadvantage is that they require even more parameters to be tuned.

5.4.3 Adaptive Penalty Functions:

Bean & Hadj–Alouane, (1993) proposed an adaptive penalty method which uses feedback from the search process. This method was first demonstrated on multiple-choice integer programming problems with one constraint. This method allows either an increase or a decrease of the imposed penalty during evolution as shown below:

$$f_p(x,k) = f(x) + \sum_{i=1}^{m} \lambda_k d_i^k$$

where λ_k is updated every generation *k* as shown:

$$\lambda_{k+1} = \begin{cases} \lambda_k \beta_1, & if\ previous\ generations\ have\ only\ infeasible\ best\ solution \\ \lambda_k / \beta_2, & if\ previous\ generations\ have\ only\ feasible\ best\ solution \\ \lambda_k, & otherwise \end{cases}$$

This formulation involves the selection of two constants, β_1 and β_2 where $\beta_1 > \beta_2 > 1$ and $\beta_1 \neq \beta_2$ (to avoid cycling), to adaptively update the penalty function multiplier, and the evaluation of the feasibility of the best solution over successive intervals of *k* generations.

In other words, the penalty component λ_{k+1} for the generation (*k* + 1) is decreased if all the best individuals in the last *k* generations were feasible or is increased if they were all infeasible. If there are some feasible and infeasible individuals tied as best in the population, then the penalty does not change.

Some of the disadvantages of this method are that there is a certain level of difficulty in setting the parameters of this penalty method. An interesting aspect of this approach is that it tries to avoid having either an all-feasible or an all-infeasible population. Another drawback of their approach is how to choose the generational gap (i.e., the appropriate value of *k*) that

provides reasonable information to guide the search. More important yet is how we define the values of β_1 and β_2 to penalize fairly a given solution. More recent constraint-handling approaches pay a lot of attention to these issues.

5.4.4 Death Penalty Functions:

As we have discussed there are many different techniques that has been developed to exploit the information contained in infeasible individuals. Many penalty functions have been implemented in GAs optimization with several major approaches emerging. The easiest way to handle the constraints is by rejection of infeasible individuals. This penalty function method is called as "Death Penalty Function". This death penalty method heuristic is a popular option in many evolutionary techniques such as Genetic Algorithms. The rejection of infeasible individuals offers a few simplifications of the algorithm: for example, there is no need to evaluate infeasible solutions and to compare them with feasible ones. The normal approach taken is to iterate recursively, generating a new point at each recursive call, until a feasible solution is found. The method of eliminating infeasible solutions from a population may work reasonably well when the feasible search space is convex and it constitutes a reasonable part of the whole search space (e.g., evolution strategies do not allow equality constraints since with such constraints the ratio between the sizes of feasible and infeasible search spaces is zero)

The formulation for Death Penalty function with *m* constraints as mentioned by Kuri & Quezada, (1998) is shown below. The fitness of an individual is determined using;

$$fitness_i(X) = \begin{cases} f(X) & if\ the\ solution\ is\ feasible \\ K - \sum_{i=1}^{s} \left(\frac{K}{m}\right) & Otherwise \end{cases}$$

$$where, \quad K \rightarrow \infty$$

$s = number\ of\ constraints\ satisfied$

$m = number\ of\ constraints$

In the present work these death penalty functions are used to evaluate the objective function. In death penalty function methods, individuals that violate any one of the constraints are completely rejected. No information is extracted from those infeasible individuals. This method is also computationally very efficient method, because when a certain solution violates a constraint, it is rejected and generated again. Thus, no further calculations are necessary to estimate the degree of infeasibility of such a solution.

There is an abundance of literature regarding the utilization of various penalty function methods in optimizing the complex real world problems. For instance, Coit & Smith, (1996) presented a penalty model based genetic algorithm to search for the feasible or optimal solution from a set of solution consisting of both feasible and infeasible solution. They solved 33 problems with variations with different 3 different levels of non-feasible threshold criteria. They concluded that an adaptive penalty function based genetic search yielded promising results for optimization method for solving reliability design. They further stated that this approach is powerful and robust for the redundancy allocation problem which usually has large search spaces and difficult-to-satisfy constraints. These methods proved to be excellent in terms of both final feasible solution quality and variance of the solution. In 1974 Zienkiewicz used penalty functions to modify variation principles used in the finite element analysis field to enforce constraints. This method has been illustrated on the problems of interest in elasticity and fluid mechanics. Further he concluded that, the penalty function approach is very viable and useful method for imposing constraints in the finite element context.

Dommel & Tinney, (1968) presented a model for solving the power flow problem with control variables consisting of real and reactive power to minimize the instantaneous costs of the losses by automatically adjusting transformer ratios. In this model they used a Newton's method for obtaining the minimum costs and penalty functions to penalize the functional inequality constraints. This method was applied to solve the problems of 500 nodes. In general applications of GAs in any optimization problems, constraints are mostly handled by penalty a function, which penalizes the infeasible solutions by reducing their fitness values in proportion to the degrees of constraint violation. However, it is always needed to specify these coefficients at the beginning of the calculation, which is a difficult task because these coefficients do not have any clear physical meanings hence it becomes impossible to estimate their values. To address these problems existing in the penalty function methods, Nanakorn & Meesomklin, (2001) developed an adaptive penalty function method with standard GA for structural design optimization. In this method the values of the coefficients adjusts itself, throughout all generations of evolution, so that the chance to be selected into the mating pool of the best infeasible members compared with that of the average feasible members. This is achieved by setting the ratio between the fitness values of the best infeasible solutions with that of the average infeasible solutions. The method developed was tested by using three optimization problems of truss and frame structures, which yielded promising results compared to traditional approaches.

Conclusions:

Depending on the nature of individual mete-heuristics, some real-world optimization problems have constraints that cannot be taken into account explicitly, thus necessitating the use of other constraint-handling methods such as penalty functions. A variety of constraint handling techniques are introduced and explained in brief in this chapter. Although many constraints handling techniques are listed in this chapter, considering that we are going to use Death Penalty functions in the present research work, special emphasis is given to Penalty Function Methods. Each method namely, Static Penalty Function, Dynamic Penalty Function, Adaptive Penalty Function and Death Penalty Function, they all have different features and their own abilities. Each method has its own advantages and disadvantages. The most popular constraint handling method among users is penalty function methods. Depending on the type of the optimization problem, a proper technique has to be picked. Hence deciding the type of the penalty function to be used in a particular problem domain is very subjective in nature. Hence the users may have to experiment with different values of penalty parameters.

Furthermore, the fitness of the technique depends on the type of the problem solved. In the previous chapter some of the mathematical and heuristic techniques were introduced to solve optimization problem. This metaheuristic approach (namely Genetic Algorithms) along with the death penalty functions are used in the present research to determine optimal component replacement policies for the components involved in the power distribution system. This problem formulation and the problem statement along with the objective function and the fitness evaluation is mentioned in the next chapter.

Chapter 6

POWER DISTRIBUTION SYSTEM OPTIMIZATION

6.1 Introduction:

Genetic algorithms have been applied to solve problems in many difficult engineering domains and are particularly effective for combinatorial optimization problems with large, complex search spaces. Normally, real engineering problems are considered as constraint problems; however application of Genetic Algorithm (GA) to such problems is very popular. Penalty functions have been traditionally used to convert a constrained optimization problem into an unconstrained one. This approach requires a somewhat arbitrary selection of penalty functions coefficients. To understand the concepts of these tools, component replacement methods were introduced in chapter 1, the detailed understanding of electricity transmission and distribution systems were presented in chapter 2, followed by the metaheuristic approaches (emphasizing more on Genetic Algorithms) were presented in chapter 3, and penalty functions to handle the combinatorial problems constraints were presented in chapter 4. In the present research, a Genetic Algorithm is developed to obtain optimal component replacement policies for radial distribution system over the finite planning horizon subject to annual budget constraints. Death penalty functions methodology is used to eliminate the infeasible solutions from the pool of initial generated population.

In the past Yangpin *et al.,* (1999) developed a genetic algorithm to determine the fault diagnosis for nuclear power plant (NPP). In this method they have used the knowledge base to combine classical probability with GAs and experimented on the 950 MW full size simulator in the Beijing NPP simulation training center. Abdel-Magid *et al.,* (1997) developed GA model for

stabilization of a power system with a wide range of operating conditions using a single power system stabilizer. The optimization problem of selecting the parameters of the power system to stabilize the set of power plants were solved by using a GA and an eigenvalue based objective function. The main objective was to minimize the state vector subject to the constraints of stabilizer gain and time constant. A single-machine infinite bus system was used to demonstrate this technique. In this work the robust power system stabilizer design was formulated as a single objective function problem, and not all parameters were considered adjustable hence to solve this problem Magid & Abido, (2003) extended this work formulating it as a multi-objective problem to optimize the system comprising of the damping factor and damping ratio of the electromechanical modes.

Coit & Smith, (1996) developed and demonstrated a reliability optimization model for series-parallel systems and to determine the optimal design configuration of the subsystems. In this model they used GA to evaluate the objective function of minimizing the cost and maximizing the reliability of the system under consideration. In this method they have also used dynamic penalty functions to penalize the infeasible solutions. Bris *et al*., (2003) developed an optimization method to minimize the preventive maintenance (PM) cost of series-parallel systems based on the time dependent Birnbaum importance factor using Monte Carlo simulation and GAs. In their research they have used GAs to find the best maintenance policy using a simulation approach to assess the availability of the series-parallel structure thus optimizing, for each component of a system, the maintenance policy minimizing the cost function, with respect to the availability constraint and mission time. Later, Samrout *et al*., (2005) has extended the model developed by Bris *et al*., (2003) solving the problem using Ant Colony Optimization (ACO). In this they have replaced the GAs used in Bris *et al*., (2003) with ACO to calculate the

solution vector of series-parallel system component inspection periods and then compared the results of both algorithms via cost and time evaluations.

In 1994, Sundhararajan & Pahwa presented a new optimization method to determine the optimal selection of capacitors to be placed in radial distribution system. The selection criterion was based on the size, type, location, and the number of capacitors to be placed in the radial system. Genetic algorithm was proposed to minimize the peak power losses and the energy losses in the radial distribution system subject to the cost of the capacitor to be placed in the system and sensitivity analysis was performed to determine the candidate locations for placing the capacitors in the system. They tested the solution methodology with a 9-bus system and a 30-bus system. Later, Levitin, *et al.,* (2000) proposed a model on the basis of Sundhararajan & Pahwa, (1994) to determine the optimal allocation of capacitors in the distribution system. In this method the capacitor placement in the distribution system was based on the customers having different load patterns. They developed a genetic algorithm using an integer encoding technique which allowed them to represent the types and the allocation of the capacitors in the same integer string. The main objective was to find the optimal placement of the capacitors in the distribution network with respect to type and allocation, subject to feeder voltage constraints. This methodology was applied and tested on the single distribution feeder network fed from the substation transformer.

In 2001, Gallego *et al.,* solved similar type of capacitor placement problem in radial distribution system. In this methodology, they presented a hybrid Tabu Search approach using the features of Genetic Algorithm and Simulated Annealing approaches. They also performed sensitivity analysis and tested this methodology on 9-bus, 69-bus, and 135-bus system. Kim *et al.,* (2003) solved the similar capacitor placement problem; the main objective was to improve

voltage profile and minimize power losses. They presented an elite-based simples GA hybrid approach combined with multipop-GA (ESGA) and applied to IEEE 13-bus and 34-bus test systems. Similar kind of capacitor placement problems were solved using GA's in Masoum *et al.,* (2004), Hybrid method using Ant Colony Search (ACS) and was compared with the results obtained from Hybrid Differential Evolution (HDE), Simulated Annealing (SA) and Ant System (AS) in Chiou *et al*., (2004), Mixed-Integer Linear Optimization in Khodr *et al*., (2008), Ant Colony Search Algorithm (ACSA) in Chang, (2008) and Discrete Particle Swarm Optimization (DPSO) in Ziari *et al*., (2010). In the present research, a Genetic Algorithm is developed to obtain component replacement model for power distribution system over the finite planning horizon; the model developed is applied to a Radial Configuration which is most commonly used configuration in power industry. The main objective is to minimize the total cost of the replacement of the components subject to budget constraints.

6.2 Power Distribution System Assessment for Total Cost of Replacement:

In the component replacement schedules the main objective is to minimize the total cost of the overall planning horizon of the components in the power distribution system. The total cost takes into account the maintenance cost, unavailability cost and the purchase cost of the component depending on the various decisions (Keep, Replace) as explained in the following sections.

6.2.1 Calculating Component Failure Rate:

In the present research work, N.H.P.P (Non-Homogeneous Poisson Process) is been utilized to evaluate the current age of the component in the power grid. Non Homogeneous Poisson process

(NHPP) is often used as a model for systems whose failure rate varies with time. A NHPP is a generalization of a Homogeneous Poisson Process where events occur randomly over time at an average rate of λ events per unit time. The rate at which events occur in a NHPP varies with time as determined by the intensity function, λ (t), which is an integral function of time, Arkin *et al.,* (2000). In the present work, the Crow/AMSAA (Army Material System Analysis Activity) model is used to determine the aging (increasing failure rates) for the different components in the power distribution system [Espiritu & Coit, 2007] and [Coit, 1998].

The failure intensity function for each component *l* in the system is given by,

$$E_l[N(\tau)] = \lambda_l \tau^{\beta_l} \tag{1}$$

$$\mu_l(\tau) = \lambda_l \beta_l \tau^{\beta_l - 1} \tag{2}$$

The expected number of failures by age τ on any one year time interval of the component is calculated by;

$$\lambda_{i,j}(\tau) = \lambda_l\left[(\tau+1)^{\beta_l} - \tau^{\beta_l}\right] \tag{3}$$

6.2.2 Calculating Maintenance Cost and Unavailability Cost of the Components:

The maintenance cost is the cost required in maintaining a particular component in the power grid during its maintenance schedule. Moreover, the maintenance operation reduces the effective age of the component by stated percentage of its actual age however it does not affect the failure rate of that particular component. The equations to determine the maintenance cost and the

unavailability cost of the i^{th} component in j^{th} planning period can be is given below in equation (4) and equation (5) respectively;

The maintenance cost of the component is calculated by using the following equation;

$$M_{i,j}(\tau) = \lambda_{i,j}(\tau).C_i \quad (4)$$

The unavailability cost is the cost associated with the unavailability of the electricity to the customers due to the network shutdown during the system maintenance operation or during the system upgrades. Basically this is the cost incurred due to the losses faced by the supplier when they fail to supply the electricity to the customers.

The unavailability cost of the component is calculated by using the following equation;

$$U_{i,j}(\tau) = \lambda_{i,j}(\tau).r_{i,j}.I_t \quad (5)$$

The objective function with N number of components and planning horizon K is formulated as;

$$F_K = min \sum_{i=1}^{N} \sum_{j=1}^{K} [M_{i,j}(\tau) + U_{i,j}(\tau) + P_{i,j}] \quad (6)$$

subject to,

$$M_{i,j}(\tau) + U_{i,j}(\tau) + P_{i,j} \leq B_j$$

The notations used are as follows;

$N(\tau)$	Number of observed failures in $(0, \tau)$
τ_0	Initial age of a component at the beginning of planning horizon (when $t = 0$)
τ	Asset or Component Age
μ_l	Failure intensity (sometimes called instantaneous failure rate)
λ_l	N.H.P.P Parameter
β_l	N.H.P.P Parameter
$\lambda_{i,,j}(\tau)$	Failure rate of i^{th} component during j^{th} period (component age of τ years)
$M_{i,j}(\tau)$	Maintenance Cost of i^{th} component during j^{th} period with the age of τ years
$U_{i,j}(\tau)$	Unavailability Cost of i^{th} component during j^{th} period with the age of τ years
$P_{i,j}$	Purchase Cost of the NEW i^{th} component during j^{th} planning period
B_j	Total Budget Allocation during j^{th} planning period
$r_{i,j}$	Repair Time of i^{th} component during j^{th} planning period
C_i	Cost of Minimal Repair for i^{th} component during j^{th} planning period
I_t	Customer Interruption Cost *(this value is constant = 1500 ($/Hr))*

Usher *et al.*, 1998 [74] proposed a model to predict a cost-optimal preventive maintenance policy for a repairable system with an increasing rate of occurrence of failure. In this model they have divided the maintenance planning horizon into n discrete and equally sized periods. And for each period, they proposed three possible actions (namely, Maintain the system, Replace the system, do nothing to the system) such that the total net present worth of all future costs are minimized.

6.3 Algorithm Developed

A new dynamic GA was developed to obtain the replacement schedules for the components of power distribution system; Figure 32 shows the flowchart of the developed algorithms followed by a brief description of the algorithm is given below:

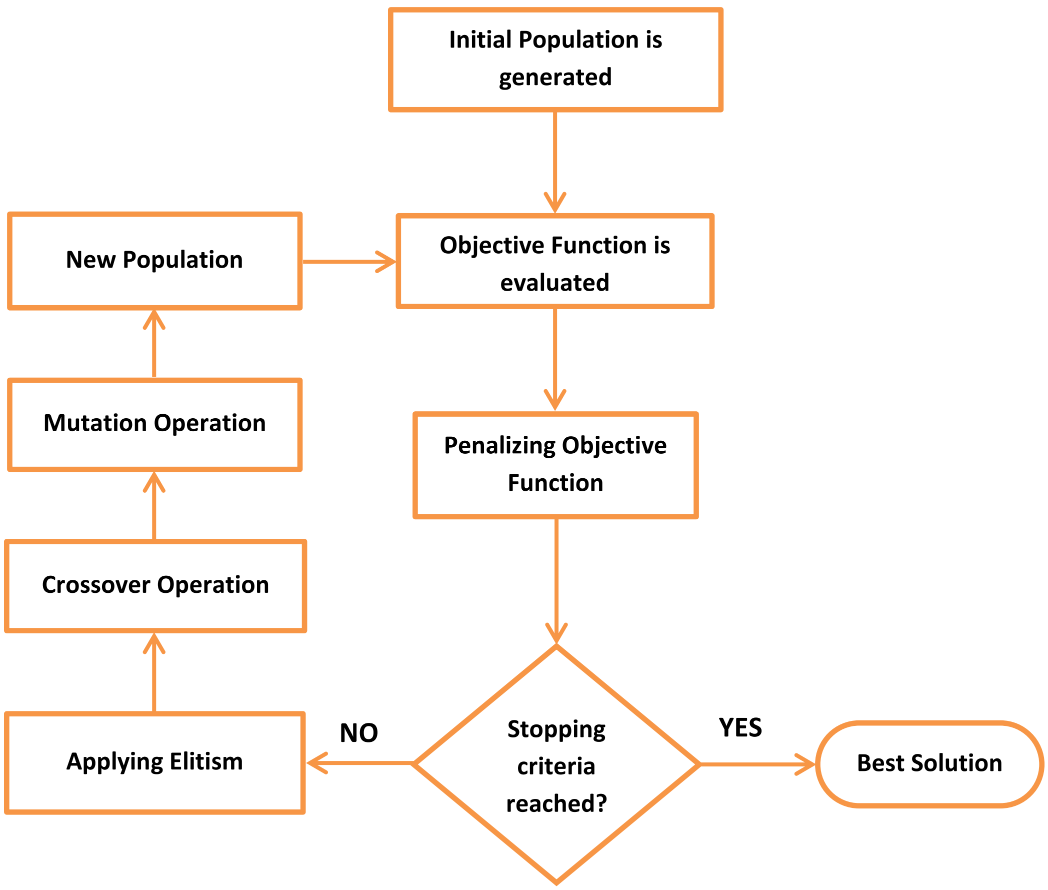

Figure 32: Genetic Algorithm Flowchart

1) **Chromosome representation**:

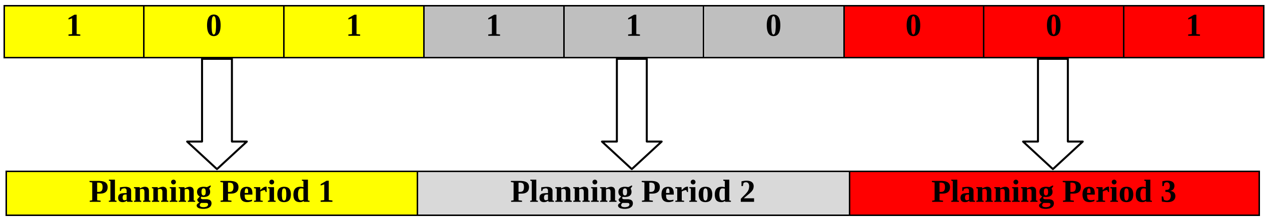

Figure 33: Chromosome Representation

In the above chromosome representation 1 denotes KEEP decision and 0 denotes REPLACE decision. When we encounter 1 in the chromosome then it's a KEEP decision for that particular component and when we KEEP that particular component we will incur total of Maintenance Cost and Unavailability Cost (in this case Purchase Cost will be ZERO because we didn't do any purchase). Furthermore, when we encounter 0 in the chromosome then it's a REPLACE decision for that particular component and when we REPLACE that particular component with new component we will incur total of Purchase Cost of that particular component and also Unavailability Cost (in this case since the component is NEW it doesn't incur Maintenance Cost hence Maintenance Cost is ZERO).

2) **Evaluation:** For each chromosome generated in step 1, the different parameters of the system are evaluated. (e.g., the maintenance cost, unavailability cost, purchase cost, and total cost of the policy).

3) **Penalty functions:** The objective function is penalized by using the death penalty function method. Once the objective function is penalized they are sorted from the best to the worst.

4) **Elitism:** The chromosomes are differentiated with elitism function in the ratio of 30:70. However this factor can be changed according to the problem to be solved.

5) **Crossover:** The best chromosomes (solutions generated so far) are selected and crossover operation is performed on these chromosomes to create new solutions to be used in the next generation.

6) **Mutation:** Some of the new elements in the population undergo mutation.

7) **New Population:** A new population is formed and the problem goes to step 2 and several iterations are performed until a specified stopping criterion is satisfied, such as the number of generations.

6.4 Example Problem:

The physical structure of most power systems consists of generation facilities feeding bulk power into a high-voltage bulk transmission network, which in turn serves any number of distribution substations. A typical distribution substation will serve from one to as many as ten feeder circuits. In the present work, the model developed is applied to electric distribution network to find component replacement policies over a finite planning horizon subject to budget constraints.

Distribution networks are typically of two types, radial or interconnected. As shown in the fig a radial network leaves the station and passes through the network area with no normal connection to any other supply. This is typical of long rural lines with isolated load areas. An interconnected network is generally found in more urban areas and will have multiple connections to other points of supply. The benefit of the interconnected model is that in the event of a fault or required maintenance a small area of network can be isolated and the remainder kept on supply.

In the present work, the algorithm developed is applied to a radial configuration as shown in the Figure 34. The main objective is to find the replacement schedules of the components

included in this network. This is carried out by using the direct evaluation technique in which the number of components *N* and also the number of planning periods *K* is entered. Further details like the size of the population, the budget amount, and tolerance level are also a part of user input.

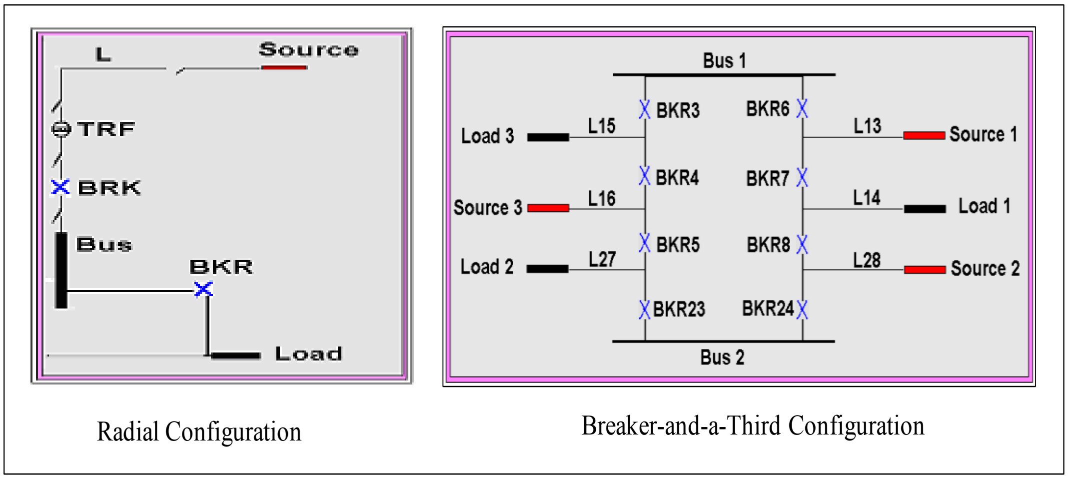

Figure 34: Radial and Interconnected electricity distribution networks

The inflation rate of 1% is used to project the inflation for the following budget schedule. The algorithm evolves to find the chromosome with the minimum cost which lies within the budget amount specified. The resultant string is the replacement schedule consisting *(N x K)* bits which represents the replacement schedules of *N* components for *K* planning periods.

Example 1:

In this example, the model developed is applied to the radial system shown in Figure 35. This system consists of 6 components, however for initial tests the developed GA model is applied to only 4 components in the system to obtain their optimal replacement schedules over a planning period of 10 years. The components are Line 13.8kV, Breaker 13.8kV, Line 600ft and a Switch. Table 2 presents the problem parameters. Typical average outage rates and other data were used from various sources.

Table 2: Component Data for Example 1

Component	Asset initial age (τ_0)	λ_i (Outages/year)	β_i	$r_{i,j}$ (Hours/Outage)	C_i ($/Outage)	P_i ($)
1) Line 13.8kV	**20**	**1.9560**	**1.25**	**1.32**	**1500**	**45,000**
2) Breaker 13.8kV	**10**	**0.0036**	**1.60**	**83.12**	**1000**	**35,000**
3) Line 600 ft	**40**	**0.0055**	**1.80**	**26.51**	**1900**	**33,300**
4) Switch	**35**	**0.0061**	**1.85**	**5.60**	**700**	**10,000**

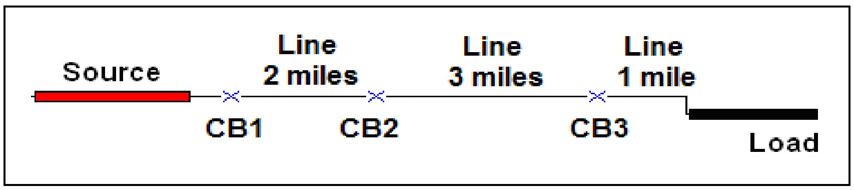

Figure 35: Radial Configuration for Example 1

In this example, the replacement schedule is determined for N=4 components over the planning period of K=10. The initial population size was 1000 and the annual budget amount was set to be equal to $200,000. The algorithm was run for 50 generations with the probability of crossover of 0.65 and the mutation probability of 0.02.

<table>
<tr><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>0</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>0</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td></tr>
<tr><td colspan="4">Period 1</td><td colspan="4">Period 2</td><td colspan="4">Period 3</td><td colspan="4">Period 4</td><td colspan="4">Period 5</td><td colspan="4">Period 6</td><td colspan="4">Period 7</td><td colspan="4">Period 8</td><td colspan="4">Period 9</td><td colspan="4">Period 10</td></tr>
</table>

Figure 36: Recommended Chromosome for the Radial System 1

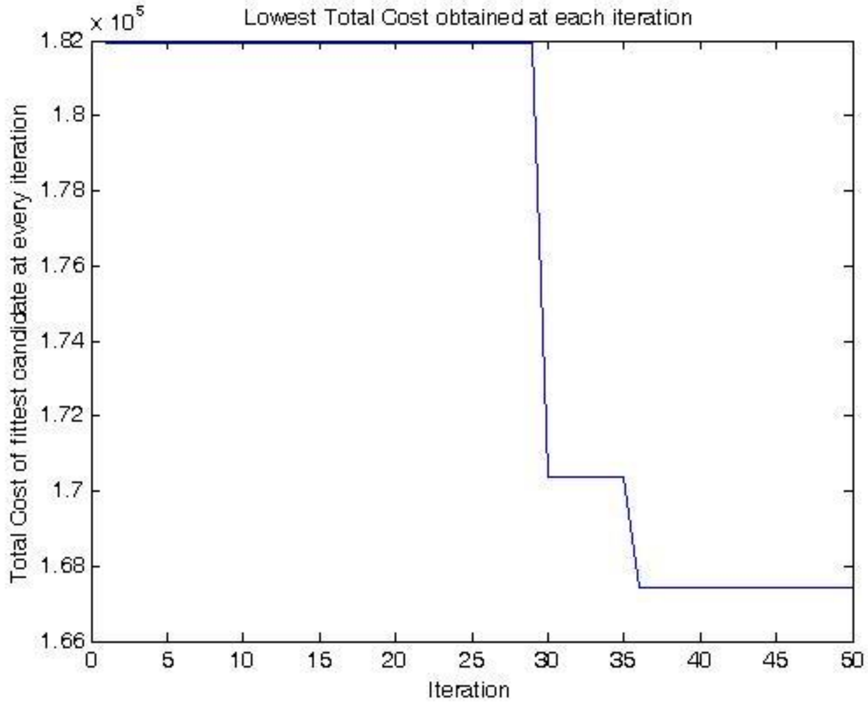

Figure 37: Graph showing the lowest total cost obtained at each interval

Figure 36, shows the results for the replacement schedules for the above mentioned components over the period of 10 years. And the graph in the Figure 37 shows the total cost of the fittest candidate obtained after evaluation of all the possible solutions at the end of each interval. The final system level component replacement for the radial system configuration in above example is given in the Table 3. The algorithm is run for 50 generations and the lowest total cost obtained at the end of 50^{th} generation is $167,416.

Table 3: Component Replacement Schedules for Example 1

	Planning Period									
Component Name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Line 13.8kV	0	1	1	1	1	1	1	1	1	1
Breaker 13.8kV	1	1	1	1	0	1	1	1	1	1
Line 600 ft	0	1	1	1	1	1	1	1	1	1
Switch	1	1	1	1	1	1	0	1	1	1

Example 2:

This example presents a larger and more complex system with (N = 9) components. These components replacement schedules are obtained for the planning period of (K = 10) years. The initial population size was 1000 and the annual budget amount was set to be equal to $450,000. The algorithm was run for 50 generations with the probability of crossover = 0.65 and the mutation probability = 0.02. The model is applied to the radial configuration in Figure 39. The problem data is presented in the Table 3.

Table 4: Component Data for Example 2

Component	Asset initial age (τ_0)	λ_l (Outages/year)	β_l	$r_{i,j}$ (Hours/Outage)	C_i ($/Outage)	P_i ($)
1) Line 300 ft	37	0.0047	1.80	23	1900	17500
2) Breaker 480 V	10	0.0045	1.95	20	780	16000
3) Line 600 ft	30	0.0066	1.76	23.55	1900	33300
4) Switch	31	0.0162	1.32	6.30	650	10000
5) Transformer	45	0.0043	1.55	345	3000	30000
6) Breaker 13.8kV	15	0.0099	1.87	20	700	35000
7) Bus	45	0.0044	1.27	44	3000	45000
8) Breaker 480 V	12	0.0032	1.91	22	900	17500
9) Line 600 ft	49	0.0057	1.88	28	1900	33300

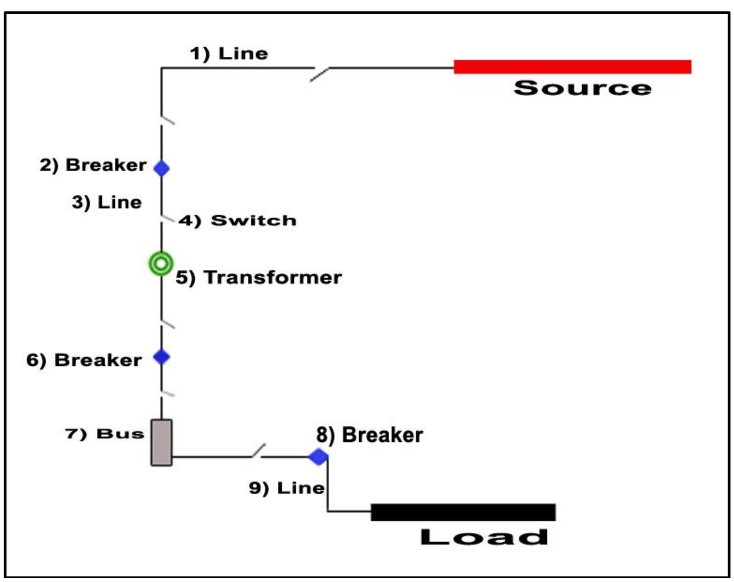

Figure 38: Radial Configuration for Example 2

1	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**1**	**0**	**1**	**0**	**1**	**1**	**1**
Period 1									**Period 2**									**Period 3**								
1	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Period 4									**Period 5**									**Period 6**								
1	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Period 7									**Period 8**									**Period 9**								
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**																		
Period 10																										

Figure 39: Recommended Chromosome for the Radial System 2

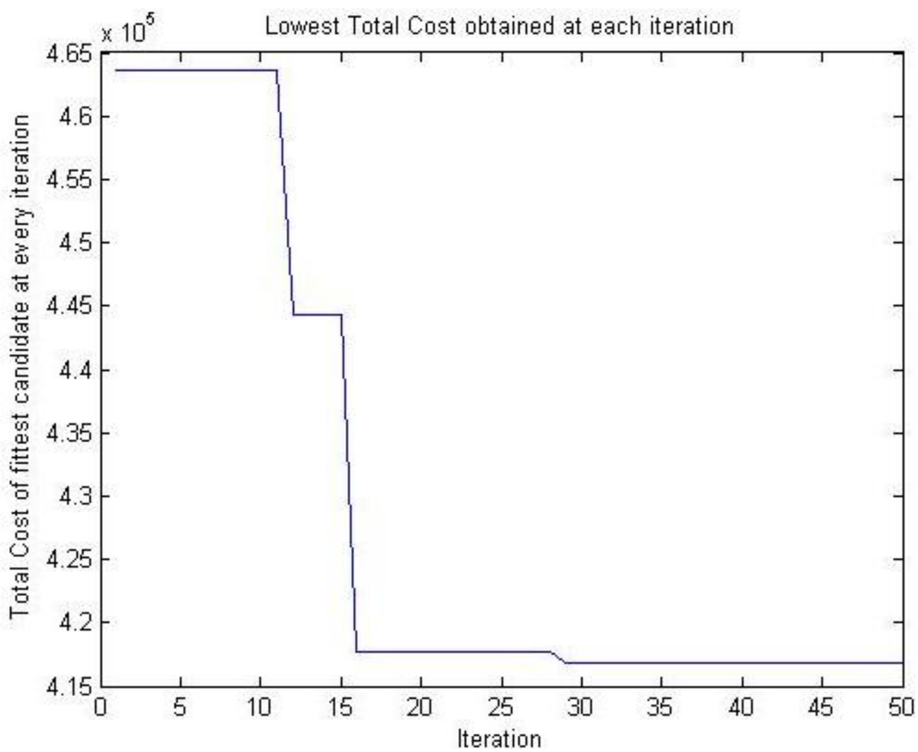

Figure 40: Graph showing the lowest total cost obtained at each interval

Table 5: Component Replacement Schedules for Example 2

	Planning Period									
Component Name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Line 300 ft	1	1	0	1	1	1	1	1	1	1
Breaker 480 V	1	1	1	1	1	1	1	1	1	1
Line 600 ft	1	0	1	1	1	1	1	1	1	1
Switch	1	1	0	1	1	1	1	1	1	1
Transformer	1	1	1	0	1	1	1	1	1	1
Breaker 13.8kV	1	1	0	1	1	1	1	1	1	1
Bus	0	1	1	1	1	1	1	1	1	1
Breaker 480 V	1	1	1	1	1	1	0	1	1	1
Line 600 ft	0	1	1	1	1	1	1	1	1	1

Figure 40, shows the recommended chromosome for the radial system in Figure 39. And the graph in Figure 41 shows the total cost of the fittest candidate obtained after evaluation of all the possible solutions at the end of each interval. The final system level component replacement for the radial system configuration in above example is given in the Table 5. The algorithm is run for 50 generations and the lowest total cost obtained at the end of 50th generation is \$416,845.

6.5 Conclusions & Future work:

A dynamic GA method for determining the replacement schedules for components in the power distribution systems subject to annual budget constraints was developed and presented in this research. The model developed is a dynamic model in which a user is prompted to specify the number of components existing in the system (to be solved) along with the number of planning periods to determine the replacement policies for those components under consideration. This makes the model more flexible and robust so that it can be applied to radial distribution network of a significantly large number of components involved in that system.

A generalized formulation for the component replacement policies pertaining to power systems problems in which various issues such as objectives and constraints commonly encountered in the real-world power distribution systems were examined. A generalized framework is developed for utilization of GAs to obtain optimal component replacement schedules for power systems. Death penalty functions were used to penalize the infeasible solutions. This method is applied and tested on two different radial configurations of power distribution system, which is a common configurations used in most areas. The component replacement schedules were obtained and the total cost of the policy obtained lies well within the allocated budget amount.

The examples presented is been applied to radial system configurations. In general these systems are composed of small number of components; hence the future work would be to consider the extension of the component replacement model to solve more complex power distribution configurations such as breaker-and-a-half, breaker-and-a-third, IEEE bus system, etc. These more complex configurations will have more complex equations which will be a harder problem to evaluate. Another extension would also be considered as applying the same

model to solve different network systems such as in the field of communication which is usually a very complex network and where the size of the problem increases exponentially as the number of nodes increases in the network.

The work presented in this research is a single objective single constraint optimization problem where the objective is to minimize the total cost of the component replacement subject to the annual budget constraints. Another extension would be to consider more than one objective and constraints thus shaping the problem as a multi-objective optimization problem. Thus increasing the complexity of the problem and testing the performance of the algorithm for these multi-objective optimization problems.

Another extension will be using the Ant Colony Optimization metaheuristic to solve the same radial configuration component replacement problem and comparing the results of both methods on the basis of the performance of these two metaheuristics with respect to the quality of the solutions obtained and also the computing time required to obtain the optimal solution to this problems.

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