COLD LOAD PICKUP IN POWER DISTRIBUTION SYSTEM

A DISSERTATION

Submitted in partial fulfillment of the
requirements for the award of the degree
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in

ELECTRICAL ENGINEERING

(With Specialization in System Engineering and Operations Research)

By

SRINIVASA RAO MACHARLA

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE-247 667 (INDIA)

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INDIAN INSTITUTE OF TECHNOLOGY
ROORKEE-247667

CANDIDATE'S DECLARATION

I hereby declare that the work, which is being presented in this dissertation entitled **"Cold Load Pickup in Power Distribution System"** in the partial fulfillment of the requirement for the award of the degree of **Master of Technology in Electrical Engineering** with specialization in **System Engineering and Operations Research,** submitted in the **Department of Electrical Engineering, Indian Institute of Technology Roorkee,** Roorkee, is an authentic record of my own work carried out during July 2005 to June 2006 under the supervision of **Prof. Hari Om Gupta,** Department of Electrical Engineering, IIT Roorkee, Roorkee.

I have not submitted the matter embodied in this dissertation for award of any other degree.

Date: 22 June 2006

(SRINIVASA RAO MACHARLA)

Place: Roorkee

CERTIFICATE

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

Prof. Hari Om Gupta
Professor,
Department of Electrical Engineering,
Indian Institute of Technology Roorkee,
Roorkee – 247667,
India

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(SRINIVASA RAO MACHARLA)

ABSTRACT

Thermostatically controlled electrical devices contribute a major portion of the entire power demand of a power distribution system. Restoration of these systems after prolonged outage produces higher load demand than the preoutage load. This condition is known as cold load pickup.

The situation arises owing to loss of diversity. Due to loss of diversity of loads, the restoration of distribution feeders after long interruptions creates cold load pickup conditions. As a result, the total load briefly exceeds the substation transformer rated load. In order to prevent overheating of these transformers, the distribution system load may have to be restored in a step-by-step manner using sectionalizing switches.

In this work we have taken a distribution system (Roorkee) from this network data we have calculated loading limits of the transformer as well as minimum restoration time of the network by using different algorithms (GA & ACO) and finally checking the convergence of these methods. The distribution system (Roorkee) data is analyzed with comparison of delayed exponential model given by author. The ambient temperature has been taken from National Institute of Hydrology for finding the transformer loss of life. The loss of life is checked with IEEE Std. C57.92.1981.

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CHAPTER-1
INTRODUCTION

1.1 GENERAL

Distribution systems deliver power to various kinds of loads (Residential, Commercial, and Industrial) such as air conditioners, lighting, heating, and various electronic equipments. These loads can be classified as cyclic or non-cyclic loads. Cyclic loads are those that draw power intermittently and at somewhat evenly spaced intervals. Examples of such loads include air conditioners, refrigerators, space heaters, water heaters, etc [1].

These loads are usually thermostatically controlled. On the other hand, non-cyclic loads, such as lighting or washing machines, display no such regularity. They are often manually controlled by the consumer. During normal operating conditions in the distribution system only a fraction of the cyclic loads consume power at a time. In other words, under normal conditions, load diversity within the distribution system is established. The aggregate load on the substation is significantly less than the sum total of all the load ratings. The ratings on the substation transformers are chosen keeping this situation in view. However, when power is restored to a system following an extended power outage, there is a tendency for all cyclic loads to turn on simultaneously. As a result, the diversity of the loads is lost and undiversified load demand may be much higher than the distribution substation capacity during restoration [1].

Thermostatically controlled devices contribute a major portion of the entire power demand of a power distribution system. Restoration of these systems after prolong shut down produces a very high load demand than the normal condition load. This condition is known as **cold load pickup (CLPU)** [2]. This situation arises because of loss of diversity. During the normal operation all the connected loads never switched on or off simultaneously and diversity is maintained. But if a system faces a prolong outage then all thermostatically controlled loads get switched on simultaneously at the beginning of restoration and diversity is lost. The aggregated load reduces with time, as it is evident by different CLPU models available in literature. As it is clear by every model that the loss of diversity produces 2 to 5 time higher load than the normal load which creates violation of substation transformer loading limits, permissible voltage range of buses and current capacity of feeders [2].

The literature reveals that the CLPU came in to the picture more than sixty years ago, in 1940, but it was then not of much concern, because the enduring behavior of the load current was not so prominent, and initial phases were taken care of [3, 4]. Researchers started paying attention to this problem from late 1970s. Then, after several efforts were made in the modeling of load demands and network elements, we have seen the optimal designing of distribution networks including for CLPU, and the development of restoration techniques.

Then after several models of different types like empirical technique based, physically based, random variable model, regression model etc. were developed for CLPU [2,12-13]. In most of analytical methods of restoration, delayed exponential model [5-6] has been used. The extensive efforts to handle the problem optimally can be seen during last ten years [7-8].

Issues to handle:

1. Restoration of distribution networks under CLPU
2. Design optimization of distribution networks with CLPU

Diversity

$$\text{Diversity factor} = \frac{\text{Sum of individual maximum demands}}{\text{Maximum demand on the power station}}$$

A power station supplies power to various types of consumers whose maximum demand do not occur at the same time. Therefore the maximum demand on power station is always less than the sum of individual maximum demands of the customers. Obviously diversity factor will always be greater than 1. The greater the diversity factor, the lesser is cost of generation of power [9]. **Connected load** defined as some of continuous rating of all equipment connected to the supply system. **Maximum demand** defined as the greatest demand of load on the power station during a given period [9].

1.2 Causes of outage

The root cause of CLPU is power outages, so prevent the outages so that we can automatically control the CLPU problem [2].

- High winds blowing trees and branches onto power lines
- Vehicles striking and breaking utility poles
- High winds breaking utility poles
- High winds blowing lines into trees
- Cold-load pick-up problems
- Animals such as birds, snakes and squirrels climbing poles and contacting both pole and the power line
- Snow and ice build-up that causes power lines to break or touch tree branches
- Problems at substations

1.3 Genetic Algorithms

A genetic algorithm is a search technique used to find approximate solutions to optimization and search problems. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as natural selection, inheritance, mutation and crossover. The evolution starts from a population of completely random individuals and happens in generations. In each generation, the fitness of the whole population is evaluated, multiple individuals are stochastically selected from the current population (based on fitness), modified to form a new population, which becomes current in the next iteration of the algorithm. After a finite number of iterations, we can check the solution (encoding is done if necessary) [10].

1.4 Ant Colony Optimization

Ant communication is primarily through chemicals called pheromones. Because most ants spend their time in direct contact with the ground, these chemical messages are more developed than in other Hymenopterans. it will leave a trail along the ground, which in a short time other ants will follow. When they return home they will reinforce the trail, bringing other ants, until the food is exhausted [11].

Ants are capable of finding the shortest path from a food source to the nest. They are also capable of adapting to changes in the environment, for example, finding a new shortest path when the old one is blocked off due to a new obstacle. The main means used by ants to form and mantain the line is a pheromone trail. Ants deposit a certain amount of pheromone while walking, and each ant prefers to follow a certain direction rich in pheremone than a poorer one. This elementary behaviour of ants can be used to explain how they can find the shortest path when the sudden appearance of an unexpected obstacle has interrupted the initial path.

Ant colony optimization has been applied successfully to a large number of difficult discrete optimization problems including the traveling salesman problem, the quadratic assignment problem, scheduling, vehicle routing, etc., as well as to routing in telecommunication networks [11].

1.5 Objective of the Thesis work:

The research work is done in the area of Cold Load Pickup in power distribution network. Restoration of this power distribution network after CLPU (Outage) with minimum time for this author proposed so many methods.

- Load Modeling
- Finding the Optimal **Size and Loss of Life** of Transformer by using CLPU data collected from **Roorkee substation**.
- Applying **Genetic algorithm** to the Size and LOL optimization problem.
- Optimized the restoration time for 4-feeder and 12 sections distribution system.
- Applying **Genetic algorithm** to the non-identical section optimization problem.
- Applying **Ant Colony Optimization** to restoring the network
- Comparison of the Genetic algorithms and the proposed method Ant colony optimization for minimum restoration time.

1.6 Literature review:

The literature reveals that the CLPU came in to the picture more than sixty years ago, in 1940, but it was then not of much concern, because the enduring behavior of the load. Research has started on CLPU since 1970s. Then, after So many authors put several efforts on modeling of load demands and network elements, we have seen the optimal designing of transformer size for CLPU, and restoration techniques.

Pahwa and wakileh[5-6] suggested for system designing and restoration of network and they was taken a simplified cost function for to minimize the total cost of the system so that we can reduce the cost of the customer interruption and they had also given for transformer loss of life in IEEE std. in C52.92.1981. The paper presents a study on the optimal design of power distribution systems. Distribution substation transformer size and feeder sectionalizing switches are selected such that a cold load pickup situation can be handled while minimizing an annual cost function.

Chavali[1] giving the sequence of sectionalizing devices with minimum restoration time taken into consideration with genetic algorithms [10].

Padhy[10] demonstrated algorithms about the Genetic Algorithm and Ant Colony Optimization with suitable examples.

Kumar[2] has given full view of CLPU about causes, phases, modeling of CLPU and solution strategies also given in detail. The paper looks into the various aspects associated with the problem of CLPU and explains the phenomenon of CLPU. It reviews various modeling approaches and means of solving CLPU problems together with the affecting factors.

Agneholm[18] dissertation he was divided the total report into three parts one for residential loads, second for individual loads and one for paper and pulp industry. In each paper he has discussing different types of outages. Data on the power consumption after these outages have been used for deriving models of the cold load pick-up.

Ucak[12, 14] proposed an analytical method for restoration distribution system during CLPU condition. Delayed exponential model is used to represent the load. And also thermodynamic model has proposed for transformer loading limits and whenever loading limits are reached section are restored by step-by-method [1, 5-6, 14].

Gupta[21] described the enduring phases of CLPU and about voltage drops along the feeders. Because of CLPU condition system restoration is very difficult. The paper discusses an approach to include restoration under CPLU conditions in distribution system planning and expansion. The approach can be applied to determine the most optimal transformer size [5-6] and feeder sizes while ensuring the minimal restoration time and acceptable voltages and transformer heating during CLPU conditions.

Aoki proposes new algorithm to quickly restore the de-energized load in a distribution system by using the sectionalizing switches. In new algorithm computional burden and the solution accuracy of algorithm is improved by using concept of dual effective gradient method.

1.7 Organization of the Thesis:

This dissertation is organized in seven distinct chapters.

Chapter 1 introducing my topic

Chapter 2 details the causes of the arising of the CLPU condition, Phases of CLPU and finally hierarchical development of different load models.

Chapter3 Optimization technique which used in my programming (GA&ACO).

Chapter 4 deals with CLPU condition (with Roorkee data) and sectionalizing the network for finding the Optimal **Size and Loss of Life** of Transformer.

Chapter 5 describes step–by–step restoration method to get optimal restoration time with both GA and ACO.

Chapter 6 Results and Discussions

CHAPTER-2

CLPU and Load Modeling

General:

Here I explain about why Cold load pickup (CLPU) is coming into picture, causes of CLPU, finally phases of CLPU and after this load modeling under CLPU. In modeling we have taken temperature of the house and surrounding from we develop one model to find the CLPU behavior.

2.1 CLPU:

The main cause for CLPU is power outage. Individual loads on a residential feeder can be categorized into two groups

1. Thermostatically-controlled
2. manually-controlled.

Thermostatically-controlled devices such as air-conditioners, heaters, and heat pumps provide the largest contribution to the total load in a typical house. Manually-controlled loads are switched on and off by occupants of the house in undetermined fashion. The life-style of the occupants of the house has a significant influence on the contribution of these loads to the total load of the house. During normal conditions, diversity among loads is present, and therefore, the aggregate load of a number of houses is less than the connected load. If an abnormal condition such as an extended outage occurs in a distribution system, some or all thermostatically-controlled devices will be on as soon as the power is restored. Similarly, the aggregate load of manually-controlled devices will be higher than normal upon restoration because more people may want to use different devices. If an outage involves a large number of customers and has a long duration, it may result in excessive load during restoration. Restoring power to a circuit under such conditions is called cold load pickup (CLPU) [14].

2.2 Causes of CLPU

The power outage is the root cause for the cold load pickup condition. The outage can take place for several reasons: faults, blackouts, maintenance and extension work, forced load curtailment, lack of power transmission, generation capacity, etc. Once the power outage has taken place, the load behavior is the key factor that governs the CLPU condition [2].

2.2.1. Electric Heating and Cooling Loads

Thermostatically controlled appliances share a high portion of the total load demand. A large group of cooling and heating equipment such as refrigerators, freezers, air conditioners, water heaters, and heat radiators maintains the diversity during normal operation. During an outage the inside temperature approaches ambient temperature. Because of this, following the outage, a large number of the appliances come into the ON state by thermostat operation, and diversity is broken. The system faces higher load during this post outage period. The magnitude and duration of this demand hike mainly depends on the duration of the outage and the outside temperature. Section 4 deals with various models discussing the behavior of a thermostatically controlled load [2].

2.2.2. Electrical Illumination

Mercury lamps, high-pressure sodium lamps, and fluorescent lamps have lower power consumption subsequent to an outage than their rated power. These loads take some minutes to reach the rated values, so they ease down the CLPU problem, but the effect is nominal because of their small share in total demand [2].

2.2.3. Other Electrical Loads

Other domestic electric appliances such as stoves, ovens, washing and drying machines, electric irons, radios, and computers are used when users have a particular need. In the load demand of this group, more depends on the user's behavior and living style and is difficult to predict.

The load demand can also be categorized as industrial and residential loads. The behavior of industrial and residential loads following planned and forced outages has been analyzed, and models have been generated with the measured data [15–16]. There are other factors like weather conditions, usage statistics, outage duration, restoration procedure, and power system parameters that also affect the CLPU condition directly or indirectly.

2.3 Phases of Cold Load Pickup

On the basis of the magnitude and the duration, the CLPU current can be categorized into four phases [7]:

1. Inrush
2. Motor starting
3. Motor running and
4. Enduring phases of current

The first inrush phase is because of the flow of current to the cold lamp filament and the magnetization of the distribution transformers. The current magnitude can be up to 10 to 15 times the pre outage value, and it exists for the duration of some cycles.

In the second phase, the starting current of a motor raises the value of the current up to 6 times the normal value, and this phase sustains for about a second.

The third phase is due to the current needed in the acceleration of a motor, and this phase takes nearly 15 seconds. The first three phases last approximately in 15 seconds.

The fourth and final phase is due to the loss of diversity among thermostatically controlled loads, and it continues until the normal diversity among the loads is reestablished. The value of the duration depends upon various factors such as the weather, the use pattern, and the duration of the outage [7]. It varies from one to several hours. The load current in this enduring phase may vary from 2 to 5 times the diversified load value. It can also be seen in the literature that some authors have divided CLPU into two phases [8, 17]. The first three are aggregated and are taken as phase one phases, whereas the fourth has been taken as phase two, which is because of the loss of diversity. Other authors only divide cold load pick-up in two phases [2]. The first phase then includes the inrush, motor starting and accelerating currents whereas the second phase is due to the loss of diversity among thermostatically controlled loads.

In figure 2.1 the power consumption of an incandescent lamp is shown and as can be seen there is initially a peak which after some periods dies out [18]. For a refrigerator and freezer combination the power consumption after two outages is shown in figure 2.2 and for a residential area the power consumption is shown after two outages in figure 2.3. These three figures can be considered to be typical examples of different phases of the cold load pick-up for residential load [18].

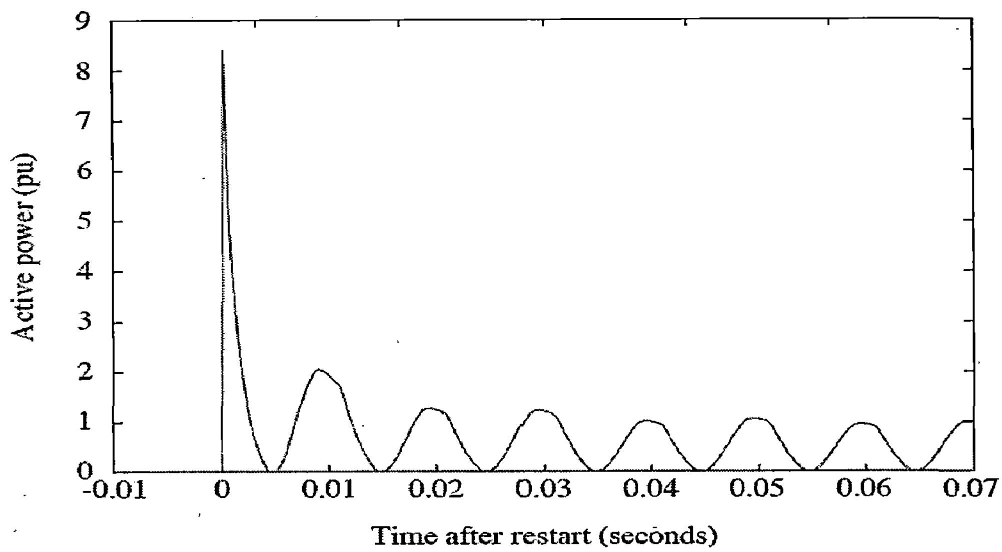


Fig: 2.1 the power consumption of an incandescent lamp after an outage.

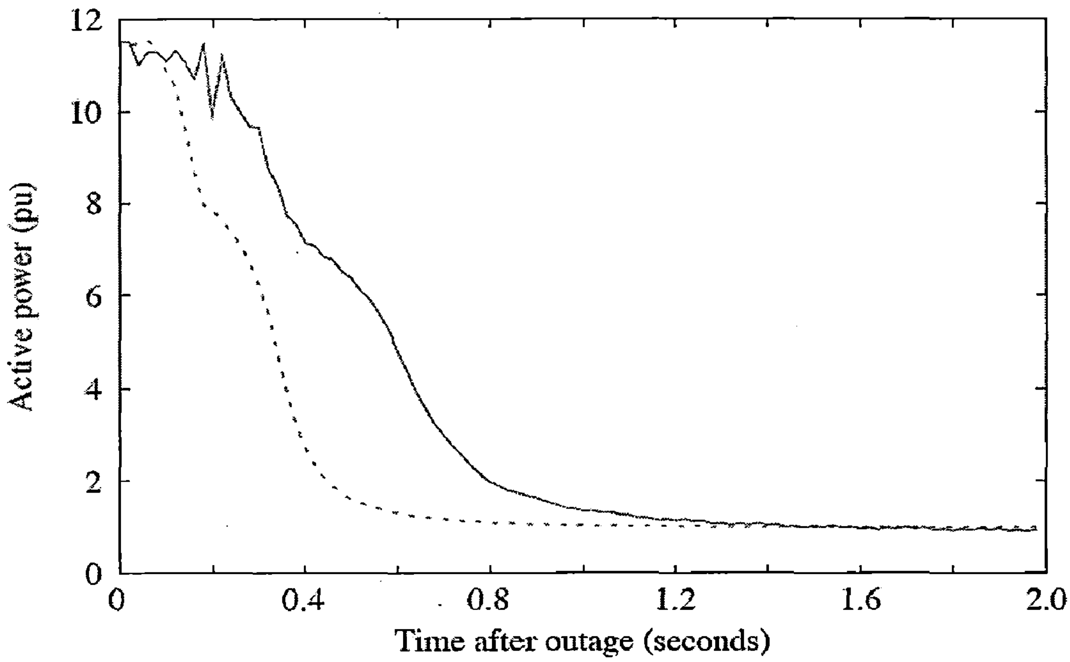


Fig 2.2 the power consumption of a refrigerator and freezer after two outages.

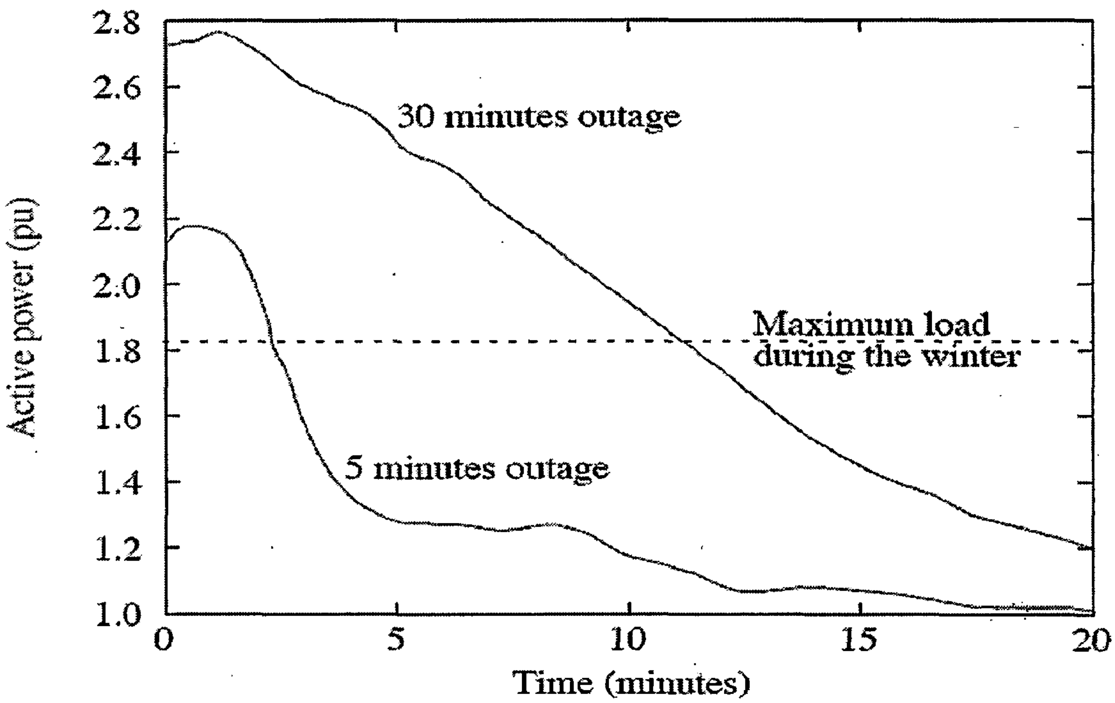


Fig 2.3 a residential area the power consumption

2.4 Load Modeling:

They are so many types modeling are proposed here I am discussing some methods given below and methods are...

- Aggregated Load Model (analytical model)
- Electric Space Heating or Cooling Loads.

2.4.1. Aggregated Load Model

This **analytical model** has been used extensively in optimization for distribution system designing because of its simple mathematical definition. It is expressed by (1), which actually shows a **delayed exponent** [12]. The difficult aspect of the work is the selection of a suitable model to represent dynamics of aggregated load for the enduring portion of CLPU. The model should be mathematically simple and yet it must account for the behavior of aggregated load as closely as possible. In extended outages, diversity is completely lost and the load is the highest immediately upon restoration. Generally, it is considered that the diversity is completely lost if the outage lasts more than half an hour. Higher than normal load may be expected for shorter outages but their effect on distribution system may not be as important as extended outages. Therefore, the aggregated load model does not need to account for the behavior of the partial loss of load diversity in the system.

In this, load change from undiversified to diversified level in the circuit may be closely represented by an exponential function. However, an exponential function model does not take into account the duration of undiversified load. It assumes that the diversity starts just after restoration. Therefore, to include the duration of undiversified load in an analytical model, a delayed exponential function is used to model CLPU behavior of aggregated loads in distribution system as shown in Figure 2.4 [12]. Also, a delayed exponential model for cold load pickup of thermostatically-controlled devices has been suggested by Anil Pahwa [5]. The Simulation results using physically based load models confirm that a delayed exponential model is a good representation of the CLPU load dynamic [12]. The delayed exponential model offers accuracy and simplicity and thus is very attractive for representing cold load pickup of thermostatically-controlled loads, particularly, if a large number of houses are considered to determine the aggregate load.

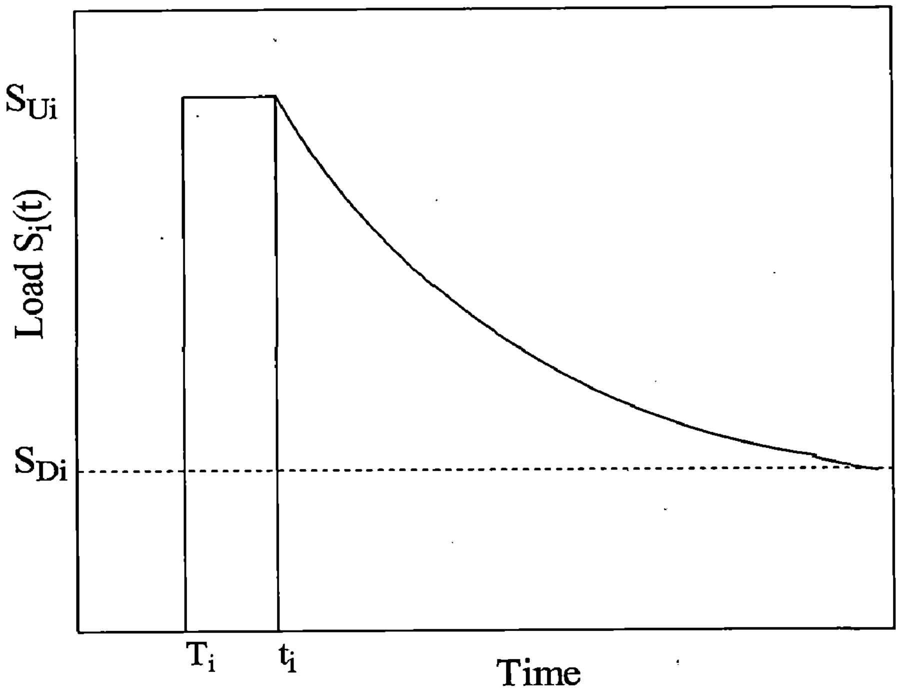


Fig 2.4 CLPU model of aggregated load of i^{th} section in distribution system

$$S_i(t) = [S_{D_i} + \left(S_{U_i} - S_{D_i}\right)e^{-\alpha_i(t-t_i)}]u\left(t-t_i\right) + S_{U_i}[1-u\left(t-t_i\right)]u\left(t-T_i\right) \quad \text{... (2.1)}$$

Where α_i is the rate of decay of load on i^{th} section, and $S_i(t)$ is load of i^{th} section. $u(t)$ is a unit step function given by (2)[2]

$$\text{u(t)}=\begin{cases} 1 \text{ for } t \geq 0 \\ 0 \text{ for } t < 0 \end{cases} \quad \text{.......... (2.2)}$$

For $T_i<t<t_i$, diversity is completely lost and all thermostatically-controlled devices are in the ON state. After t_i, devices start entering the cyclic state and the load in that section will decrease until full diversity is restored [5].

2.4.2 First Order Deterministic Model of Air Conditioner:

In this model, a discussion based on a simple model for a thermostatically-controlled load developed by **Canbolat Ucak** [12] is presented. According to this model, the temperature of a house having an air-conditioner is given by:

$$\frac{d\theta(t)}{dt} = -\frac{1}{\tau}\left[\theta(t) - \theta_a - w(t)\theta_g\right] \quad \text{.......................} (2.3)$$

The value $\theta(t)$ is the inside temperature of the house, θ_a is the ambient temperature, θ_g is the temperature gain of the air-conditioner, and τ is the time constant of the house. The variable $w(t)$ is a binary variable denoting the state of the air-conditioner (OFF=0 and ON=1.) The state changes when the temperature of the house reaches the thermostat upper or lower limit given by $\theta_s + \Delta/2$ and, $\theta_s - \Delta/2$ respectively. Heating loads will also have the same type of characteristic. The only difference is the sign of binary variable or thermostat state $w(t)$.

Figure 2.5 shows the state of thermostat and house temperature as a function of time during normal conditions. When the inside temperature of the house reaches the thermostat upper limit, air-conditioner state changes from zero to one, and when the lower limit is reached, the state changes from one to zero. During steady state condition one could define the duty cycle "D" of an air conditioner as

$$D = \frac{d_{on}}{d_{on} + d_{off}} \qquad \text{.. (2.4)}$$

Here, d_{on} is the ON duration and d_{off} is the OFF duration of thermostat during one period as shown in Figure 2.5. Average power demand of an air-conditioner can be calculated as the product of the duty cycle and the rating of the air-conditioner. Both d_{on} and d_{off} can be written as a function of out side temperature

$$d_{on} = T_{out}\text{ , } d_{off} = \Delta t$$

Gain of air-conditioner, dead band, and thermostat setting of the house [12]. A good approximation for *dw is*

$$dw = \frac{\tau\Delta(2w-1)}{\theta_s - \Delta/2 - \theta a - w(\Delta + \theta_g)} \qquad \text{........... (2.5)}$$

We get an expression for the duty cycle, which varies between 0 and 1, as a function of outside temperature and air-conditioner parameters [12]

$$D = \frac{\theta_a - (\theta_s - \Delta/2)}{\theta_g + \Delta} \qquad \text{........................ (2.6)}$$

If the ambient temperature is less then the thermostat lower limit, then the air-conditioner will be OFF all the time. An extreme case is when the outside temperature exceeds $\theta_g + \theta_s + \Delta/2$. In this case, the air-conditioner will stay ON and average inside temperature of the house will never reach the thermostat lower limit. This case corresponds to a duty cycle of one which means that the size of air-conditioner is too small to cool the house. Undersized and oversized air-conditioners could exist in a distribution system. The duty cycle of an undersized air-conditioner is closer to one whereas the duty cycle of an oversized air-conditioner is closer to zero when compared to a normal-sized air-conditioner.

The exact formula for d_w can be derived from above Equation. And thermostat upper and lower limits. The result is given by

$$dw = -\tau \frac{\theta_s + \Delta/2 - \theta_a - w(\Delta - \theta_g)}{\theta_s - \Delta/2 - \theta a + w(\Delta + \theta_g)} \quad \text{............} \quad (2.7)$$

Figure 2.6 shows the difference between the exact and approximated duty cycle as a function of ambient temperature for $\theta_s = 22$ °C, $\Delta = 3\,°\mathrm{C}$, and $\theta_g =$ 30 °C. Duty cycle changes approximately linearly in the range 25 °C to 50 °C and it does not depend on the time constant of the house. This is true since both d_1 and d_0 will be affected with the same ratio τ when changes.

In Figure 2.7 [12] the change in house temperature as a function of time during an outage of duration T_{out} is shown. In this case undiversified load duration which is shown as Δt can be calculated from a first order differential equation based on the house and air conditioner parameters.

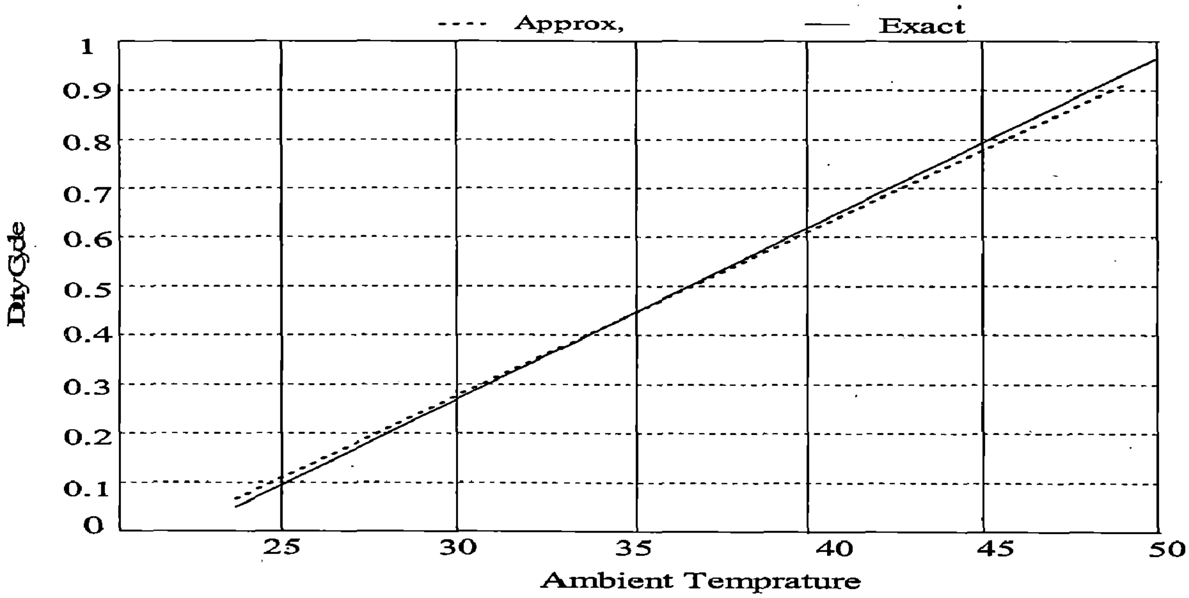


Fig 2.5 the difference between exact and approximated duty cycle as a function of θ_a

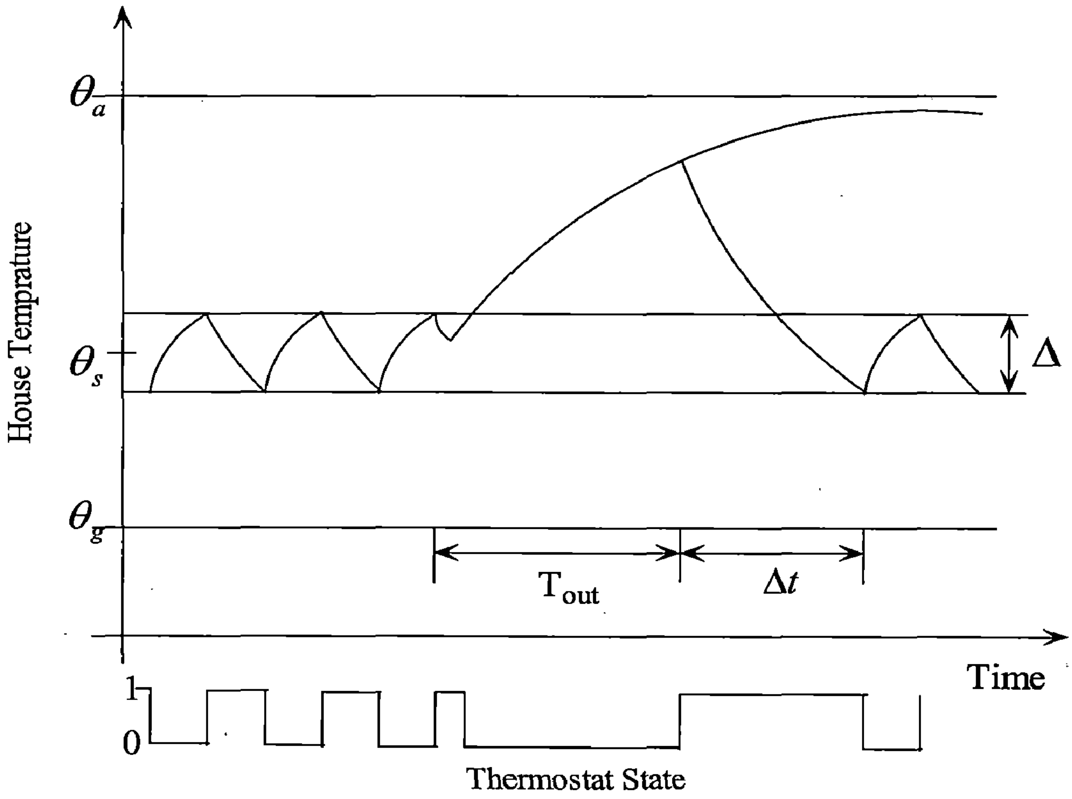


Fig: 2.6. House temperature during an outage

Let us assume that the outage occurred when the house temperature was at θ_s. After the outage, the house temperature will start to increase to target temperature, θ_a and at T_{out} the temperature inside the house becomes [12]

$$\theta\left(T_{out}\right) = \left(\theta_a - \theta_s\right)\left(1 - e^{-T_{out}/\tau}\right) + \theta_s \quad \text{.................. (2.8)}$$

When the power is restored the house will start to cool down as shown in Figure 3.3. Thermostat will change its state from one to zero when the temperature reaches $\theta_s - \Delta/2$, that is, the state will change when

$$\theta_s - \Delta/2 = \left[\left(\theta_a - \theta_s\right) - \left(\theta_a - \theta_s\right)e^{-T_{out}/\tau} + \theta_s - \theta_f\right]e^{-\Delta t/\tau} + \theta_f \quad \text{..... (2.9)}$$

$$\theta_f = \theta_a - \theta_g$$

From this above eq modified into

$$\theta_s - \Delta/_2 - \theta_f = \left[-(\theta_a - \theta_s) e^{-T_{out}/\tau} + \theta_g \right] e^{-\Delta t/\tau}$$

Take logarithms to both sides to get Δt

Undiversified load duration can be solved from this equation to give

$$\Delta t = -\tau \ln \frac{\left(\theta_s - \Delta/_2\right) - \theta_a + \theta_g}{\theta_g - (\theta_a - \theta_s) e^{-T_{out}/\tau}} \quad \text{.........................} \quad (2.10)$$

In Figure 2.8 undiversified load duration Δt as a function of outage duration. The figure shows that for very long outages, undiversified load duration has a saturation characteristic. The physical meaning of this is that the temperatures of houses reach the ambient temperature during a long outage. This also shows that using a linear relationship between undiversified load duration and outage duration may not be a correct representation of load for the wide spectrum of outage durations ranging from 30 minutes to a few hours.

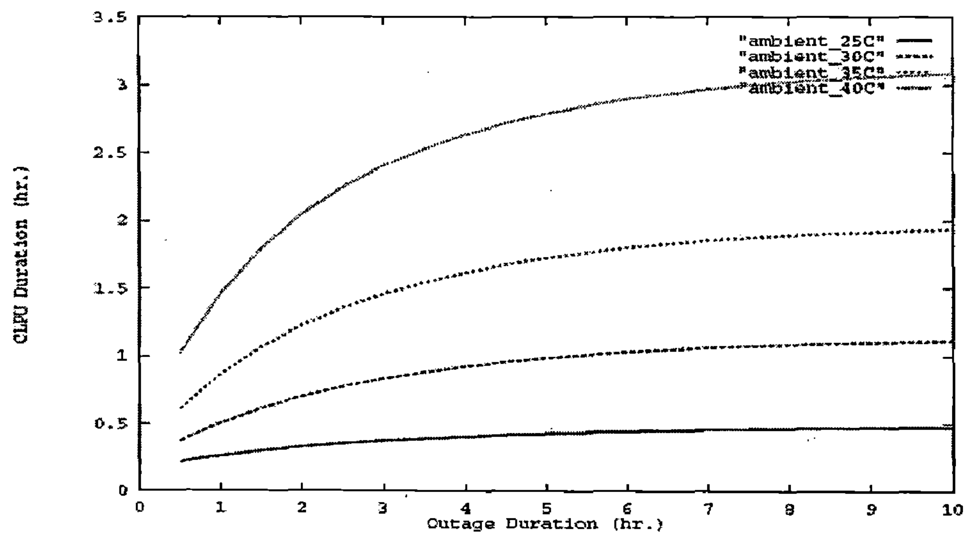


Fig: 2.7 undiversified load duration Δt as a function of outage duration

2.5 Results for modeling:

From the modeling we can get the load of the transformer and CLPU duration. Load of the transformer calculated from the aggregated model if we know the diversified and undiversified load of the transformer. From our Roorkee data Apply to this model u got...

$S_U = 2.8$ MVA,

$S_D = 9.3$ MVA,

Outage duration = 120 mints

From this the unit function is

$u(2.01-2) = u(0.01) \geq 0 = 1$, and remaining one is less than zero so it is zero

$S_i = 2.8+(9.3-2.8)e^{-(2/2)} * 1+0$

$S_i = 5.19$MVA

For getting the CLPU duration we have to use second model for this data is as follows:

τ (Time constant)= 3 hrs, θ_S (set temp)=22^{0}c,

θ_a (Ambient temp)=40^{0}c, θ_g (gain temp)= 30^{0}c,

$\theta_f = \theta_a - \theta_g = 10^0$c, $\Delta = 3^0$c ;

$\theta_S + \Delta/2 = 23.5^0$c, $\theta_S - \Delta/2 = 20.5^0$c;

$$\text{Duty cycle} = \frac{\theta_a - (\theta_s - \Delta/2)}{\theta_g + \Delta}$$

D= 40-20.5/30+3= 0.5909

$$\Delta t = -\tau \ln \frac{\left(\theta_s - \Delta/2\right) - \theta_a + \theta_g}{\theta_g - \left(\theta_a - \theta_s\right) e^{-T_{out}/\tau}}$$

$$\Delta t = -3 * \frac{20.5 - 40 + 30}{30 - 18e^{-40/180}}$$

$$\Delta t = -3 * \ln \frac{10.5}{30\text{-}14.41}$$

Δt = -3* -0.395=1.185 hrs =78mints CLPU duration

As observed in the figure given fig 2.8 in that according to outage duration CLPU duration given and above results are matched.

CHAPTER-3

METHODS

Here I am giving techniques which I have used in my thesis work. These two methods are random search techniques. The two methods are [10].

1) Genetic Algorithms (GA)
2) Ant Colony Optimization (ACO)

GA is works based on "Darwin theory of survival of the fittest". This is search algorithms based on the mechanics of natural selection and natural genetics.

ACO is finding the shortest path between source and nets (food). Ants can smell pheromones: while choosing their path, they tend to choose the paths marked by strong pheromone concentrations. The pheromone trail allows ants to find their way back to the food.

We take brief introduction about each method.

3.1 Genetic Algorithms

3.1.1 Introduction:

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures known as population with a randomized structure to form a search algorithm which resemblances the genetic nature of the human being. In every generation, a new set of artificial creatures (strings) are created using bits and pieces of the fittest of the old. From all the parents and children in the mating pool, the fittest is again selected so that after every iterations, the performance is improved. This algorithm is computationally simple yet powerful in its search for improvement [10].

The GA maintains a set of possible solutions (population) represented as a string of typically, binary numbers (0/1). New strings are produced in each and every generation by the repetition of a two-step cycle [10].

1. First step involves first decoding each individual string and assessing its ability to solve the problem. Each string is assigned fitness values, depending on how well it is performed in an environment.
2. In the second stage, the fittest string is preferentially chosen for recombination, which involves the selection of two strings, and the switching of the segments this is called crossover. Another genetic operator is mutation. It is used to maintain genetic diversity within a small population of strings. There is a small probability that any bit in a string will be flipped from '0' to '1'. This prevents certain bits from becoming fixed at a specific value due to every string in the population having the same value, often causing premature convergence to a non-optimal solution.

There are many kinds of search techniques which are classified in to calculus based, enumerative and random. Genetic algorithms are different from other normal optimization and search procedures in following ways [10].

- GAs work with a coding of the parameter set, not the parameters themselves. Therefore, they can easily handle integral or discrete variables.
- GAs use probabilistic transition rules, not deterministic rules.
- GAs search from a population of points, not a single point.
- GAs use only objective function information, not derivatives or other auxiliary knowledge.
- Sometimes near optimal solution that can be generated quickly, using Gas, are desirable than optimal solutions which require a large amount of time.

3.1.2 Tools of Genetic algorithm:

1. **Cromosome:**

   In biological terms, a cromosome means a DNA which carries genetic information in cells. Similarly in artificial cromosome (i.e. cromosome used in genetic algorithms), each element is a competitor for the final solution which carries the fitness related to the fitness function (objective function). The cromosome can be of any type (decimal, binary, octal etc..,) The cromosome format used in this thesis is a binary format and is generally represented as (16 bit cromosome)

   1011010100101010

2. **Population:**

   In genetic algorithms, the processing is not done on a single cromosome, but on a set of cromosome, which is called population. The population is updated for each and every iteration, where the population of the current iteration has children which are better in fitness than the population in the previous iteration [10].

   General form of population is

$$\text{Population} = \begin{bmatrix} Cromosome1 \\ Cromosome2 \\ . \\ . \\ cromosome'n' \end{bmatrix}$$

   Where 'n' is the population size (pop size).

3. **Crossover rate:**

   In the mating pool, different cromosomes are selected for crossover based on some selection criteria. Crossover rate is the rate at which the number of cromosomes that are selected for crossover over the total number of cromosomes present in the mating pool.

$$Crossover\ rate = \frac{Number\ of\ cromosomes\ selected\ for\ crossover}{Total\ number\ of\ cromosomes\ \text{in}\ the\ matingpool}$$

4. **Mutation rate:**

To avoid some abnormal conditions which show direct effect on the convergence of the algorithm, we will mutate the cromosomes, based on mutation rate. Mutation rate is the number of cromosomes that are selected for mutation over the number of cromosomes present in the mating pool [10].

$$Mutation\ rate = \frac{Number\ of\ cromosomes\ selected\ for\ mutation}{Total\ number\ of\ cromosomes\ \text{in}\ the\ matingpool}$$

3.1.3 Genetic Representation:

Encoding:

Representing or encoding the problem in hand when applying GA is a vital task. Genetic representation of a cromosome is called encoding. There are a few ways of encoding the chromosomes, such as integer, real-valued but one of the most popular ways is binary encoding (bit string), because it is a simpler string to operate [10].

For binary encoding each chromosome is constructed by stringing binary representations of vector components. The length of each chromosome depends on the vector dimension and the desired accuracy. A sample binary representation is shown here.

S = 1010101111101011

An ‘n’ bit string can represent integers from 0 to 2^n-1 i.e. 2^n integers.

The main advantage of binary encoding is that it maximizes for greater sampling of the solution space. The other kinds of encoding include octal encoding, hexadecimal encoding etc..,

Decoding [10]

In order to retrieve original information from the cromosome, it must be decoded to its original format. If a cromosome (S) in binary format is considered, the decoding value of the binary string is

$$\sum_{k=0}^{k=n-1} 2^k S_k \quad \text{.................................. (3.1)}$$

The original value of X, the integer is

$$X = X_L + \frac{(X_U - X_L)}{(2^n - 1)} \text{ X decoded value of the string} \quad \text{................. (3.2)}$$

A simple genetic algorithm:

Genetic algorithm has got a simple structure, basically consisting of three operators.

1. Reproduction/Selection.
2. Crossover.
3. Mutation.

The primary step prior to the start of genetic algorithm is the initialization of the tools of the GA (population, crossover rate etc..,). The next step is reproduction.

3.1.4 Reproduction:

Reproduction is the first operator applied on population. Reproduction is a process in which individual strings are copied according to their objective function values, *f*. Cromosomes are selected from the population to be parents to crossover and produce offspring. Strings with higher value of fitness have more probability to be selected from the mating pool. Hence this process is also called selection.

Roulette wheel selection:

This selection procedure is so called because it works in a way that is analogous to a roulette wheel. Each individual in a population is allocated a share of a wheel, the size of the share being in proportion to the individual's fitness. A pointer is spun (a random number generated) and the individual to which it points is selected. This continues until the pre-requisite number of individuals has been selected. An individual's probability of selection is thus related to its fitness ensuring that fitter individuals are more likely to leave offspring [10].

First the fitness values are then calculated using the fitness function for each chromosome V_i (i=1....pop size). The total fitness of the population is given by

$$F = \sum_{i=1}^{popsize} fitesss\ fun(V_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

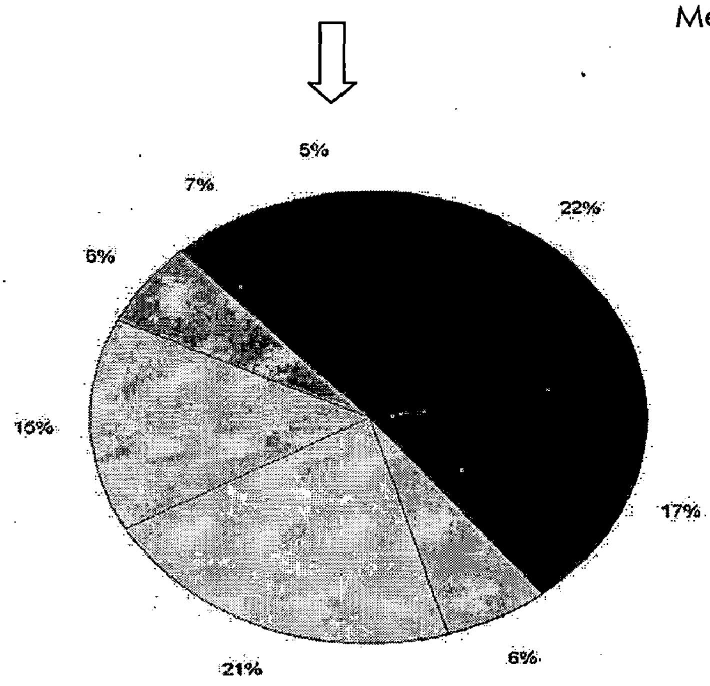
The probability of selection for each chromosome V_i (i=1... pop size) is

$$P_i = \frac{\text{fitnessfun(Vi)}}{\text{F}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

And the cumulative probability is

$$Q_i = \sum_{j=1}^{i} P_j \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

A roulette wheel is constructed with the cumulative probabilities of all the cromosomes. A cromosome with greater fitness function will have more probability and hence will be selected number of times to the mating pool. The selection process is based on spinning the roulette wheel pop size times, each time selecting a single chromosome for the mating pool.



In the Simulation of Roulette wheel, a random number is generated between 0 and 1 and the cromosome is selected such that the generated random number is in the arc of the cumulative probabilities.

3.1.5 Crossover Algorithms:

Crossover is a process where two cromosomes are mixed in different means to produce two different off-springs. After the process of reproduction/selection, the parents in the mating pool are selected for crossover. The selection of parents is purely based on random techniques and the number of parents selected for crossover is decided by crossover rate which is defined before the genetic algorithm [10].

Single-point crossover:

The most basic crossover algorithm is Single Point Crossover. A random number is generated which indexes the bits along the string and the strings are swapped over at this index to form two new off-springs.

Parent 1: **1 0 0$_1$ 1 1 1 0 1** $\Rightarrow$ Child1 = **1 0 0 0 1 0 0 1**

Parent 2: **1 1 0$_1$ 0 1 0 0 1** Child2 = **1 1 0 1 1 1 0 1**

Multi-point crossover:

Multipoint crossover algorithms extend simple crossover by selecting multiple crossover points and swapping the part of the two chromosomes between these two random numbers.

Parent1: **1 0 0$_1$ 1 1 1$_1$ 0 1** $\Rightarrow$ Child1 = **1 0 0 0 1 0 0 0**

Parent2: **1 1 0$_1$ 0 1 0$_1$ 0 0** Child2 = **1 1 0 1 1 1 0 1**

Mutation Process:

Mutation is a process in which a bit is taken from a chromosome at random and flips that bit from '0' to '1' or vice-versa. The selection of chromosome from the mating pool is also random. Mutation is done mainly to deal two special cases.

1. If all the chromosomes in the mating pool are equal, the crossover produces children which are identically equal to the parents. Due to this, the convergence is never achieved.
2. If bits of all the chromosomes are either zeros or ones, mutation helps to get convergence.

To simulate mutation, two random numbers are required, one for selection a particular chromosome in the mating pool and second one is to select a particular bit in the chromosome to flip that bit.

Before mutation = **1 1 0 1 1 1 0 1**

After mutation = **1 1 0 0 1 1 0 1**

At the end of the two processes, crossover and mutation, the population is updated with the new population, the update must be in such a manner that the new population must have good finesses when compared to old population.

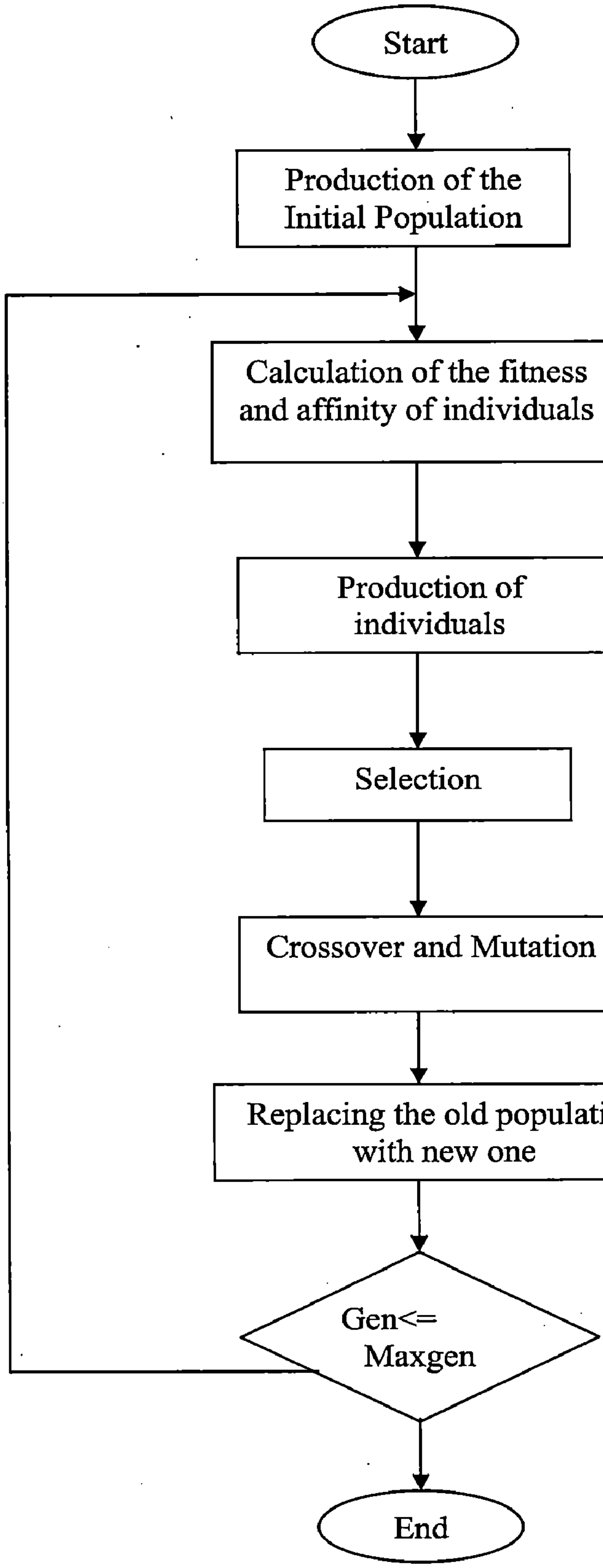


Fig 3.1 Flow chart for genetic algorithms

3.2 Ant Colony Optimization

Ants are one of the most successful groups of insects in the animal kingdom and are of particular interest because they are a social insect and form highly organized colonies or nests, sometimes consisting of millions of individuals. Colonies of invasive ant species will sometimes work together and form super colonies, spanning a very wide area of land [11].

Ant communication is primarily through chemicals called pheromones. Because most ants spend their time in direct contact with the ground, these chemical messages are more developed than in other Hymenopterans. It will leave a trail along the ground, which in a short time other ants will follow. When they return home they will reinforce the trail, bringing other ants, until the food is exhausted.

Ants are capable of finding the shortest path from a food source to the nest. They are also capable of adapting to changes in the environment, for example, finding a new shortest path when the old one is blocked off due to a new obstacle. The main means used by ants to form and mantain the line is a pheromone trail. Ants deposit a certain amount of pheromone while walking, and each ant prefers to follow a certain direction rich in pheremone than a poorer one. this elementary behaviour of ants can be used to explain how they can find the shortest path when the sudden appearance of an unexpected obstacle has interrupted the initial path [11].

Ant colony optimization has been applied successfully to a large number of difficult discrete optimization problems including the traveling salesman problem, the quadratic assignment problem, scheduling, vehicle routing, etc., as well as to routing in telecommunication networks.

However, when they act as a community, they are able to solve the complex problems emerging in their daily lives through mutual cooperation. This emergent behavior of self organization in a group of social insects is known as swarm intelligence, which has four basic ingredients

(a) Positive feedback

(b) Negative feedback (e.g., saturation, exhaustion, competition)

(c) Amplification of fluctuations (e.g., random walk, random task switching)

(d) Multiple interactions (Bonabeau et at, 1999).

Swarm intelligent systems are hard to program since the paths to problem solving are not predefined, but emergent in the system itself due to the interactions between individuals, those between individuals and their environment, or the behavior of the individuals themselves. An important and interesting behavior of ant colonies is their foraging behavior and, in particular, ability to find the shortest paths between food sources and their nests. While walking from food sources to their nest and vice versa, ants deposit a chemical substance called pheromone on the ground. Forming in this way a pheromone trail. The sketch shown in the Fig. 3.2 gives a general idea of the pheromone trail [10].

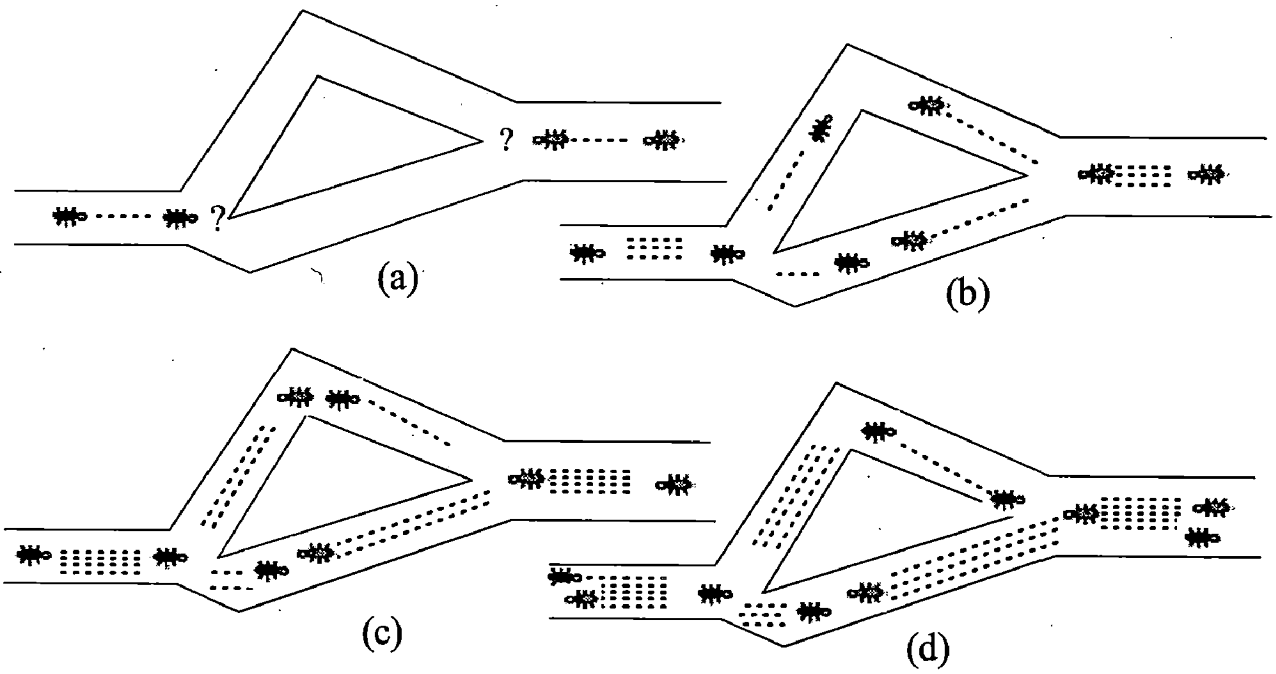


Fig 3.2 how real ants find a shortest path. (a) Ants arrive at a decision point. (b) Some ants choose the upper path and some the lower path. The choice is random. (c) Since ants move at approximately a constant speed, the ants which choose the lower, shorter, path reach the opposite decision point faster than those which choose the upper, longer, path. (d) Pheromone accumulates at a higher rate on the shorter path. The number of dashed lines is approximately proportional to the amount of pheromone deposited by ants.

3.2.1 Development of the Ant Colony System

The ant system (AS) was the first example of an ant colony optimization (ACO) algorithm and, in fact, originally a set of three algorithms called ant-cycle, ant density, and ant-quantity. These three algorithms were proposed in Dorigo's doctoral dissertation (Dorigo 1992). While in ant-density and ant-quantity, ants can update the pheromone trail directly after a move from one node to an adjacent one, in ant- cycle the pheromone update was carried out only after all the ants had constructed their tours and the amount of pheromone deposited by each ant was set to a function denoting the tour quality. Since ant-cycle performed better than the other two variants, it was later simply called ant system, while the other two algorithms were no longer studied [10].

The major merit of the AS, whose computational results were promising but not competitive enough as compared to other more established approaches, was to stimulate a number of researchers to develop extensions and improvements of its basic ideas so as to produce more performing, and often state-of-the-art, algorithms. The ACO meta-heuristic was defined a posteriori with the goal of providing a common characterization of this new class of algorithms and a reference framework for the design of new instances of AGO algorithms (Dorigo et al. 1996; Dorigo &Gambardella 1997 [24-25]).

3.2.2 Applications of Ant Colony Intelligence

There are now numerous successful implementations of the ACO meta-heuristic applied to a number of different combinatorial optimization problems. Looking at these implementations, it is possible to distinguish between two classes of applications [10]

1. Static combinatorial optimization problems and
2. Dynamic combinatorial optimization problems

Also, classification-rule-based problems as well as problems where decision making is very important are being tried out and are showing significant improvement. Researchers are trying to use ACO in hybrid models, which are a combination of different intelligent techniques.

3.2.3 Static Combinatorial Optimization Problems

Static problems are those in which the characteristics of the problem are given once and for all when the problem is defined, and do not change while the problem is being solved. The application of the ACO meta-heuristic to a static combinatorial optimization problem is more or less straightforward, once a mapping of the problem is defined, which allows the incremental construction of a solution; a neighborhood structure and a stochastic state transition rule are locally used to direct the constructive procedure. A strictly implementation-dependent aspect of the ACO meta-heuristic regards the timing of pheromone updates. In ACO algorithms for static combinatorial optimization, the way ants update pheromone trails changes across algorithms: any combination of online step-by-step pheromone updates and online delayed pheromone updates is possible.

A typical example of such problems is the classic traveling salesman problem in which city locations and their relative distances are a part of the problem definition and do not change at run-time. Other applications such as quadratic assignment, job shop scheduling, vehicle routing, sequential ordering, graph coloring, and shortest common super-sequence are seine combinatorial optimization problems that have been successfully implemented.

3.2.4 Dynamic Combinatorial Optimization Problems

Dynamic combinatorial optimization problems are defined as functions of some quantities whose values are set by the dynamics of an underlying system. The problem changes therefore at run-time and the optimization algorithm must be capable of adapting online to the changing environment. A paradigmatic example is the problem of network routing. Research on the applications of ACO algorithms to dynamic combinatorial optimization problems has focused mainly on communication networks. This is primarily due to the fact that network optimization problems have characteristics like inbuilt information and computation distribution, non-stationary stochastic dynamics, and asynchronous evolution of the network status, which well match those of the ACO meta-heuristic. In particular, the ACO approach has been applied to routing problems such as connection-oriented network routing and connection-less network routing. Routing is one of the most critical components of network control and concerns the network-wide distributed activity of building and using routing tables to direct data traffic.

3.2.5 The working of Ant colony systems:

Essentially, an ACS algorithm performs a loop, applying two basic procedures:

- specifying how ants construct or modify a solution for the problem in hand, and
- Updating the pheromone trail.

The construction or modification of a solution is performed in a probabilistic way. The probability of adding a new term to the solution under construction is, in turn, a function of a problem-dependent heuristic and the amount of pheromone previously deposited in this trail. The pheromone trails are updated considering the evaporation rate and the quality of the current solution.

3.2.5.1 Probabilistic Transition Rule

In a simple ACO algorithm, the main task of each artificial ant, similar to their natural counterparts, is to find a shortest path between a pair of nodes on a graph on which the problem representation is suitably mapped. Let G = (N, A) be a connected graph with n = [N] nodes. The simple ant colony optimization (S-ACO) algorithm can be used to find the solution to a shortest path problem defined on the graph G, where a solution is a path on the graph connecting a source node **S** to a destination node **D** shown in Fig. 3.3, and the path length given by the number of loops in the path to each arc (i, j) of the graph is associated with a variable called an *artificial pheromone trail.* At the beginning of the search process, a small amount of .pheromone τ_0 is assigned to all the arcs. Pheromone trails are read and written by ants. The amount (intensity) of a pheromone trail is proportional to the utility, as estimated by the ants, of that arc to build good solutions. Each ant applies a step-by-step constructive decision policy to build the problem's solution. At each node, local information maintained in the node itself and/or in its outgoing arcs is used in a stochastic way to decide the next node [10].

The decision rules of an ant k located in node i use the pheromone trails τ_{ij} to compute the probability with which it should choose node j $\in$ N_i as the next node to move to, Where N_i is the set of one-step neighbors of node i:

$$p^{k}_{ij} = \begin{cases} 0 & \text{if } j \in N_i \\ \tau_{ij} \Big/ \sum_{j \in N_i} \tau_{ij} & \text{if } j \notin N_i \end{cases} \qquad \text{.................. (3.6)}$$

3.2.5.2 Pheromone Updating

While building a solution, ants deposit pheromone information on the arcs they use. In S-ACO, ants deposit a constant amount $\Delta\tau$ of pheromone. Consider an ant that at time t moves from node i to node j. It will change the pheromone value τ_{ij} as follows:

$$\tau_{ij}(t) \leftarrow \tau_{ij}(t) + \Delta\tau \qquad \text{.............................. (3.7)}$$

Using this rule, which simulates real ants' pheromone deposits on arc (i.j), an ant using the arc connecting node i to node j increases the probability that other ants will use the same arc in the future. As in the case of real ants, autocatalysis and

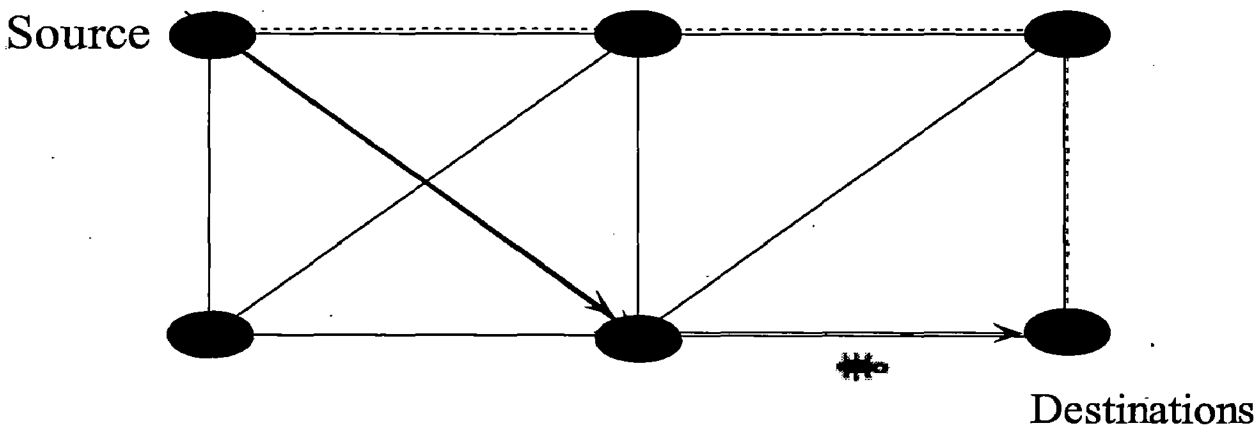


Fig. 3.3 Building of solutions by an ant from the source to the destination node

differential path length are at work to favor the emergence of short paths. To avoid a quick convergence of all the ants towards a sub-optimal path, an exploration mechanism is added: similar to real pheromone trails, artificial pheromone trails evaporate. In this way, the pheromone intensity decreases automatically, favoring the exploration of different arcs during the whole search process. The evaporation is carried out in a simple way, decreasing pheromone trails exponentially,

$$\tau=(1-\rho)\tau, \rho\in(0,1) \quad \text{.........................} \ (3.8)$$

in each iteration of the algorithm. The way the pheromone trail is updated can be classified mainly into three types as detailed below **Online step-by-step pheromone update** When moving from node i to neighboring node j, the ant can update the pheromone trail t on the arc (i, j).

Online delayed pheromone update Once a solution is built; the ant can retrace the same path backward and update the pheromone trails on the traversed arcs.

Off-line pheromones update Pheromone updates performed using the global information available are called off-line pheromone updates.

CHAPTER-4

SIZE AND LOSS OF LIFE OF TRANSFORMER

To find out the size and LoL (loss of life) of transformer we need data for cold load pickup, so I have taken the data from substation (jadugar Road and Piran Kaliyar in Roorkee) which is 8MVA, 11 KV and it has two sections. To find out solution for Cold load pickup as well as find out size and LoL of transformer they are so many ways authors proposed [1-2-5], methods are...

4.1 Techniques for Solving the CLPU Problem

Following an extended power outage, a fast and smooth restoration is very important. A number of restoration strategies have been adopted to cover various aspects associated with power system restoration. In the case of the CLPU condition, load demand varies with time, and the handling of high-magnitude current during restoration is the main task in controlling the CLPU problem. Depending on the situation, an appropriate technique or combination of techniques can be used. Different techniques used for the CLPU situation are discussed as follows [2].

1. Reduced Voltage
2. Sectionalizing the Network
3. Adaptive Protection

4.1.1 Reduced Voltage

The current demand depends on the distribution voltage. A reduction in service voltage can also reduce the value of the current. However, there is prescribed voltage range for service voltage, which must be followed. Hence, the control of load demand through voltage variation is restricted to a limited operation bend.

Lefebvre and Disbiens [19] have shown the impact of system voltage on CLPU by changing the voltage ±15%.

4.1.2 Sectionalizing the Network

Presently it is the commonly used method to restore a network after an extended outage. It is based on planned area-wise load curtailment to limit the peak current, i.e., step-by-step restoration. The operation is optimized so that the restoration can be performed in minimum time and at minimum cost. The method is very effective [2].

Ucak and Pahwa [12-5] derived the restoration time as a function of the restoration order and CLPU model parameters and then minimized the total restoration time and customer interruption duration, considering transformer temperature and loading limits.

4.1.3 Adaptive Protection

In case of adaptive protection, the devices that protect power systems change their characteristics or settings according to the condition of the system. As in the case of CLPU, over current relays are unable to differentiate between fault current and inrush current, so relays trip the network. If phenomenal logic associated with CLPU is incorporated in the protecting devices, it can act according to conditions. Removal of an instantaneous relay for a period of time is one of the commonly used techniques. Digital relays can be designed to adjust the characteristics according to conditions. It was observed that this technique, adapted relaying, has been used mostly for short times or initial phases of CLPU. In 1952, a study was performed to find out increased load capacity for increasing the time setting of existing relays. The adjustment of characteristics of over current relays was done by set points, so that the high current of the initial phases could be handled. Extreme inverse relays were recommended over inverse relays to achieve more time for the inrush current to subside [2].

The adaptive protection scheme can be efficiently applied with digital relays, but at the same time, the large number of in-service electromagnetic relays will have to be taken into consideration for optimal operation.

The optimization problem is finally applied to a real-life distribution feeder. Solving the problem using a **genetic algorithm,** the optimal values of the decision variables were obtained such that transformer overloading does not violate ANSI/IEEE C57.92-1981 [20] recommended limits.

4.2 Delayed Exponential model

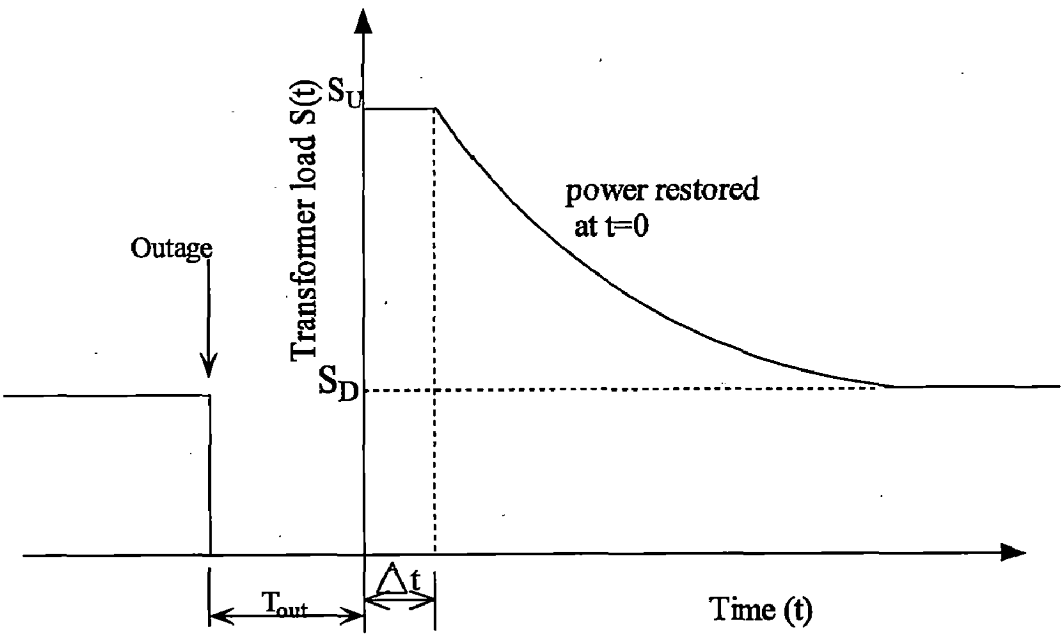


Fig.4.1. Transformer load pre and post outage

A delayed exponential model has been proposed to characterize the aggregate load during cold load pickup. Figure 4.1 shows the variation of the load with time when cold load pickup conditions persist according to this model. Here, $S(t)$ is the load as a function of time, T_{out} is the outage duration, S_U is the undiversified load, S_D is the diversified load, α is the rate of load decay, and Δ is the undiversified load duration. Following an outage, the section load reaches the undiversified maximum value S_U for duration Δ. Thereafter, the load decays exponentially towards the diversified load S_D, at a rate α [5].

The design constraints [21]:

- During normal operating conditions voltage at any service point should be within 5% of the system voltage and during emergency conditions the service voltage could range between plus 6% to minus 8% (ANSI/IEEE).
- Feeder conductors should not be loaded beyond 33% of their normal capacity
- Time of customer interruption should be minimized in case of sectional restoration.
- Transformer loss of life and temperatures should be within IEEE limits.

Ideally, a power transformer can be loaded up to its name-plate rating 24 hours a day with normal loss of life. If the distribution system experiences a peak load, for example as in a CLPU situation, overloading of transformers may be necessary for a short duration. Limitations for short term loading of 65 °C winding rise transformers are given in ANSI/IEEE C57.92-1981 [20] and they are summarized as [14]

- 4% loss of life in any one emergency operation
- 180 °C hottest-spot temperature
- 110 °C top-oil temperature
- Maximum short term loading of 2 p.u.

4.3 Optimal Size of Transformer

For finding out optimal size of transformer PAHWA [5-6] proposed one cost model on the basis of this model we find out the size and loss of Life of transformer with minimizing the cost how? It is going on from now onwards

It is desired to find the optimal size of substation transformer(s) and number of sectionalizing switches that result in minimizing a total annual cost that is broken down into the following components:

- Cost of transformers and sectionalizing switches
- Cost of energy interruption
- Revenue of energy sold during power restoration
- Cost of transformer loss of life due to overloading.

Z- is the total cost function, \$/year

X - is the number of substation transformers

S_T- is the transformer rating, MVA

$f(S_T)$- is the transformer cost function, \$/MVA.year

K_s- is the cost of a sectionalizing switch, \$/switch. year

N_S- is the number of sectionalizing switches

ρ- is the average number of extended outages per year, 1/2

K_C- is the cost of service interruption to customers,1.59 \$/kWh for residential customers and an average outage 2 hrs

TEI- is the total energy interruption, kWh/outage

K_e- is the cost of energy to customers, 0.05 \$/kWh

$E(t)$ - is the energy sold during restoration, kWh/outage

K_{lol} - is the cost of transformer loss of life, \$/outage.

Thus, our objective function can be formulated for as

$$\min Z = XS_T + f(S_T) + K_S N_S + \rho\left(K_c TEI - K_e E(t) + XK_{lol}\right) \quad \text{... (4.1)}$$

$$\begin{aligned} s.t \quad & XS_T \le S_U \\ & XS_T \le S_D \\ & \left(S_{T_m} - S_D/X\right) n > S_U - S_D \\ & 1.0 \le K_p \le 1.5 \\ & S_T, N_S \ge 0 \end{aligned}$$

S_U - is the substation total undiversified load

S_D - is the substation total diversified load

S_{T_m} - is the transformer maximum capacity, $S_{TM} = K_P S_T$

K_P - is the transformer overloading factor

n- is the total nunber of sections, $n = N_S + f$

f- is the number of feeders

Flow chart for this problem with genetic algorithm is given in appendix-A

4.3.1 Transformer Cost:

A preliminary step involves obtaining the transformer cost function. The data given in Table 1 is for a 115 kV Δ/12.47 kV Y OA/FA/FA *65 ^oC* transformer and was obtained from a utility-type transformer manufacturer. For a 12 % interest rate and a 30-year life, Burke [22] calculates the total levelized annual carrying charges factor as 20.19 %. The annual cost/MVA, shown in the fourth column of the table, has been calculated using this factor. Both linear and quadratic functions were fit to the data. These in addition to the original data points are plotted in Figure 4.2. Transformer cost can, now, be approximated as [5-6]

$$f(S_T) = K_{T0} + K_{T1} S_T + K_{T2} S^2_T$$

$$= \begin{cases} 5283.52 - 70.28 S_T \text{ , linearly} \\ 7199.263 - 235.015 S_T + 2.728\, S^2_T\text{,quadratically} \end{cases} \quad \cdots\cdots\cdots (4.2)$$

Also, taking the cost of a sectionalizing switch to be \$ 11000, one finds K_s = 2220.9.

Cost of the transformer increased as decreasing the size of the transformer and we increase size some extent it decreasing if you are increasing further cost of the transformer increased. This is how happened? That will show in appendix-A [5].

4.3.2 Distribution system:

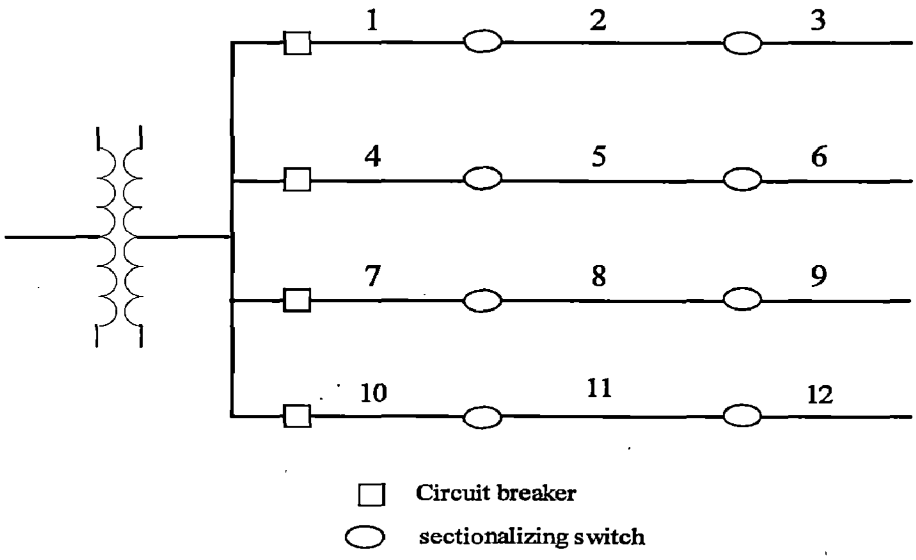


Fig 4.2 a distribution system with 4 feeders divided into 12 sections.

Background

Consider a distribution substation with x transformers that has experienced an extended outage with duration of T_{out}. If we shift our reference so that the instant power restoration starts corresponds to zero time, and with only one section being restored, then the transformer load before and after the outage will be as shown in Figure 4.1, where Δt is the undiversified load duration.

When n sections are to be restored by x transformers, each transformer would be responsible for restoring n / x of the sections. Transformer load would then be the sum of the loads of n/x sections. Based on the work of Ucak [12] and considering identical sections, the load of any section i following an extended outage would be equation (4.3)

4.3.3 Roorkee Substation Distribution system

In this distribution system [Roorkee] substation with one transformer that has experienced an extended outage with duration of T_{out}. If we shift our reference so that the instant power restoration starts corresponds to zero time, and with only one section being restored, then the transformer load before and after the outage will be as shown in Figure 4.1, where Δ **t** is the undiversified load duration.

It has 2 sections and it should be restored by one transformer only. Transformer load would then be the sum of the loads in 2 sections. Based on the work of Ucak [12] and considering identical sections, the load of any section i following an extended outage would be equation (4.3)

Roorkee distribution system:

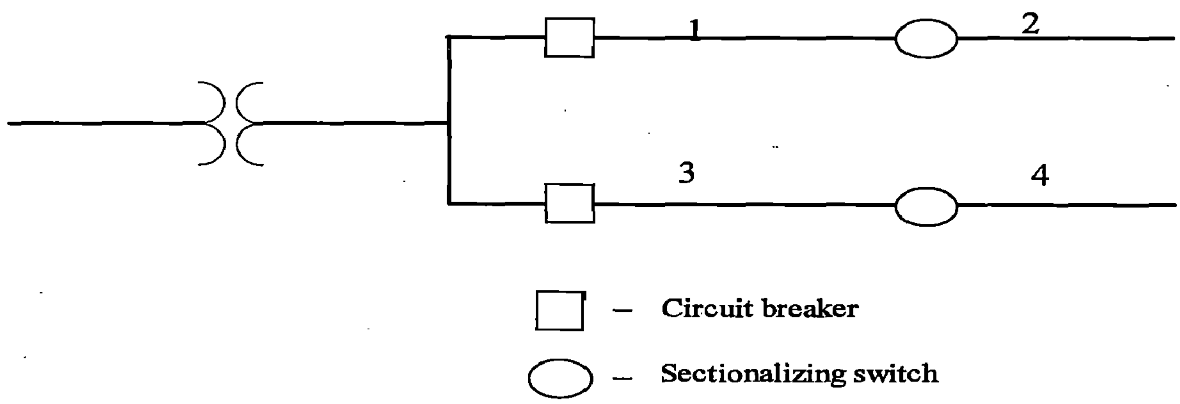


Fig 4.3 a distribution system with 2 feeders divided into 4 sections.

$$S_i(t)=\frac{1}{n}\left\{S_U\left[u(t-T_i)-u(t-t_i)\right]+\left[S_D+(S_U-S_D).e^{-\alpha(t-t_i)}\right].u(t-t_i)\right\} \quad \text{... (4.3)}$$

Where

$S_i(t)$- is the load of the i^{th} section

T_i -is the restoration time of the i^{th} section, minutes

t_i -is the time at which the load of the restored i^{th} section begins to gain diversity

α -is the load rate of decay

S_U - is the substation total undiversified load

S_D -is the substation total diversified load

n -is the total number of sections

$u(t)$ is a unit step function, $u(t) = \begin{cases} 1 & \text{for } t \geq 0 \\ 0 & \text{for } t < 0. \end{cases}$

If the transformer maximum capacity S_{Tm} is not to be exceeded, then the total number of sections restored in the first, step would be [5]

$$s = x\, Floor\left(\frac{nS_{Tm}}{S_U}\right)$$

$$S_{Tm} = K_P S_T$$

$$T_k = \begin{cases} T_K = 0 & , k \leq \frac{s}{x_0} \\ -\frac{1}{\alpha}\left\{ \ln \frac{nS_{T_m} - S_U - (k-1)S_D}{(S_U - S_D)\sum_{i=1}^{k-1} e^{\alpha(T_i+\Delta t)}}, \right. & \frac{s}{x_0} < k < \frac{n}{x_0} \end{cases} \quad \text{.......................... (4.4)}$$

4.3.4 Customer interruption and customer average interruption

Total customer interruption duration and customer average interruption duration index are, respectively, given by [5]

$$TCID = \frac{xC}{n}\sum_{i=1}^{n/x} T_i \qquad \text{(4.5)}$$

$$CAIDI = \frac{x}{n}\sum_{i=1}^{n/x} T_i \qquad \text{(4.6)}$$

Where

Variable 'C' is the total number of customers in the system.

Total energy interruption is calculated as...

$$TEI = \frac{1000xS_D pf}{60n}\sum_{i=1}^{n/x} T_i = 1000 S_D pf \frac{CAIDI}{60} \qquad \text{(4.7)}$$

Where

P_f is the power factor as measured at the distribution substation CAIDI is the customer average interruption duration, minutes. Assuming a constant power factor, the total energy supplied while *n* sections are being restored by x transformers is [5]

$$E(t) = pf\left[(S_U - S_D)\Delta t + S_D(t - \frac{x}{n}\sum_{i=1}^{n/x} T_i) + \frac{S_U - S_D}{\alpha}(1 - \frac{x}{n}\sum_{i=1}^{n/x} e^{-\alpha(t - T_i - \Delta t)})\right] \qquad \text{(4.8)}$$

4.4 LOL (Loss of Life):

Finally, Substation transformer loss of life due to overloading is taken into consideration; Temperatures inside a transformer determine its loading capability. The highest temperatures occur in the top section of transformer. Winding outlet oil temperature which is also called top-oil temperature is the hottest part of oil and average temperature of the uppermost disc is the hottest section of winding. The hottest-spot temperature is temperature of the conductor which has the maximum temperature in the uppermost disc and it is generally a few degrees higher than the average temperature of the uppermost disc. The highest deterioration of insulation material will be in the location of the hottest-spot temperature. Therefore, this temperature is used to calculate the He expectancy of a transformer [20].

Loss of life is a cumulative process. Thus, when the hottest-spot temperature is a function of time, the total loss of life for a period of T can be determined by [14]

$$\%(loss\ of\ life) = 100 \int_0^T \frac{dt}{10^{\frac{A}{\theta_{hs}(t)}+B}} \qquad \text{(4.9)}$$

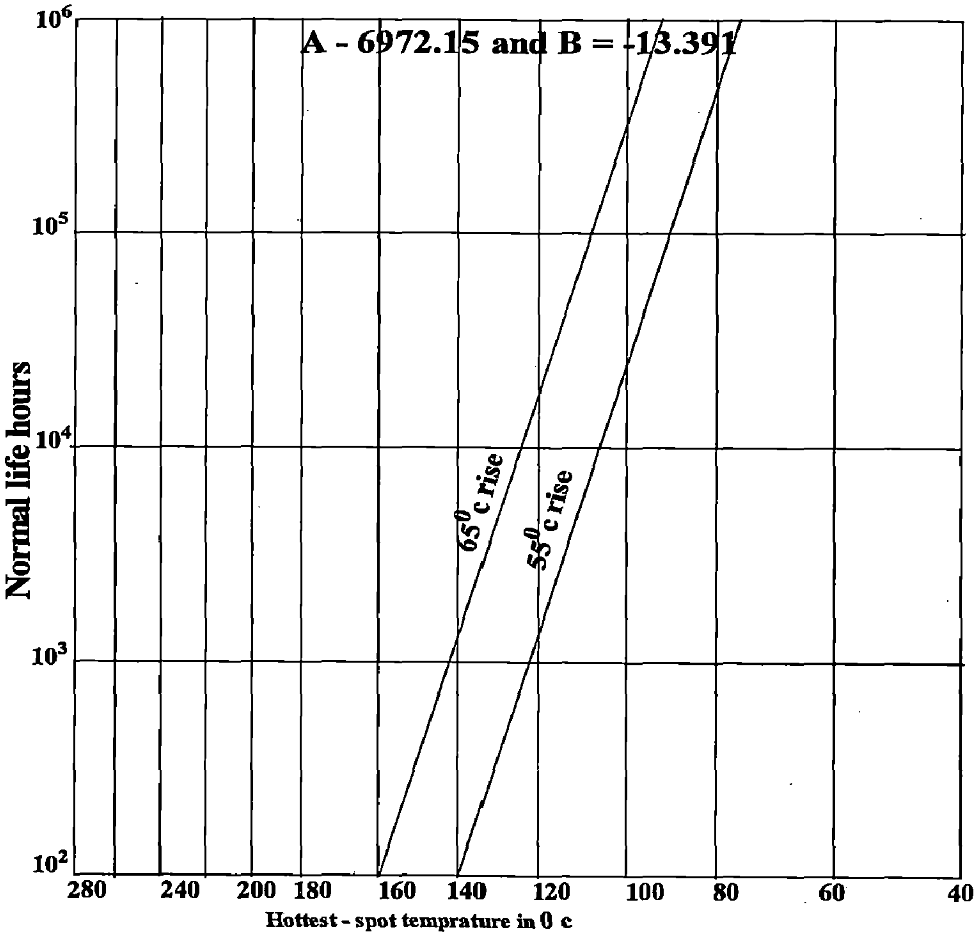


Fig 4.4 life expectancy curve [20]

Where θ_{hs} is given by

$$\theta_{hs} = \theta_a + \theta_o + \theta_g$$

And

A and B are constants from desired life expectancy curve. For 65 °C winding rise transformer, A= 6972.15 and B = —13.391 [14].

The cost of loss of life would therefore be

$$K_{lol} = \frac{S_T f(S_T)}{ACCF} \cdot \frac{LOL}{100} \qquad \text{.................. (4.10)}$$

Where ACCF is the annual carrying charges factor and its value is 0.2019.

Figure 4.6 shows during CLPU condition temperatures (top-oil and hottest-spot) changes [23].

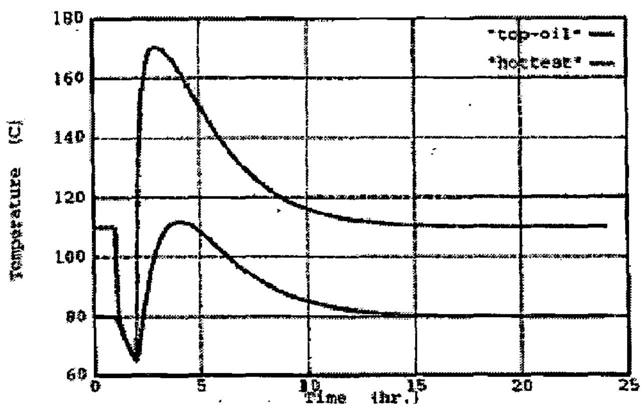


Fig 4.5 the top – oil and hottest – spot temperature during CLPU

CHAPTER-5

OPTIMAL RESTORATION TIME

General

Due to loss of diversity of loads, the restoration of distribution feeders after long interruptions creates cold load pickup conditions. As a result, the total load briefly exceeds the substation transformer rated load. In order to prevent overheating of these transformers, the distribution system load may have to be restored in a step-by-step manner using sectionalizing switches [1]. The restoration time is dependent on the order in which sections are restored. We propose genetic algorithms and ant colony algorithms as two stochastic optimization algorithms [10-11] to compute the globally best restoration sequence of sections. Both approaches belong to a class of algorithms known as evolutionary algorithms. While genetic algorithms are well known techniques for optimization, ant colony algorithms have been proposed very recently. Results obtained using both methods for two test cases are presented.

5.1 Step - by - Step Restoration

Here we have taken all section are non-identical so that each section operating at different loads. For this purpose Sudhakar Chavali [1] proposed step-by step restoration to get optimal sequence would ensure that the system is restored as quickly as possible. The distribution system used for the present study is shown in Figure 5.1. The system contains four feeders with three sections in each feeder, which are numbered.

A sequence is represented as $S = (s_1, s_2 \ldots s_n)$ where each s_j is a section number. Some of the sections in a distribution system can be restored simultaneously at the beginning if the sum total of their undiversified loads is less than the maximum allowable transformer loading, S_{MT}. Furthermore, during restoration, a section can only be restored if all prior sections located in its own feeder have already been restored. Therefore, in Figure 4.1, section 9 can be restored only after sections 7 and 8 since they are located on the same feeder. We will refer to this as the precedence constraint. Because of this precedence constraint of the restoration sequence, some of the sequences of sectionalizing switches to be turned on would be rendered invalid. For example, (1 4 5 7 6 8 9 10 11 2 3 12) is a valid sequence whereas (1 8 4 2 3 5 7 6 9 10 11 12) is not since section 8 appears before section 7 in the sequence.

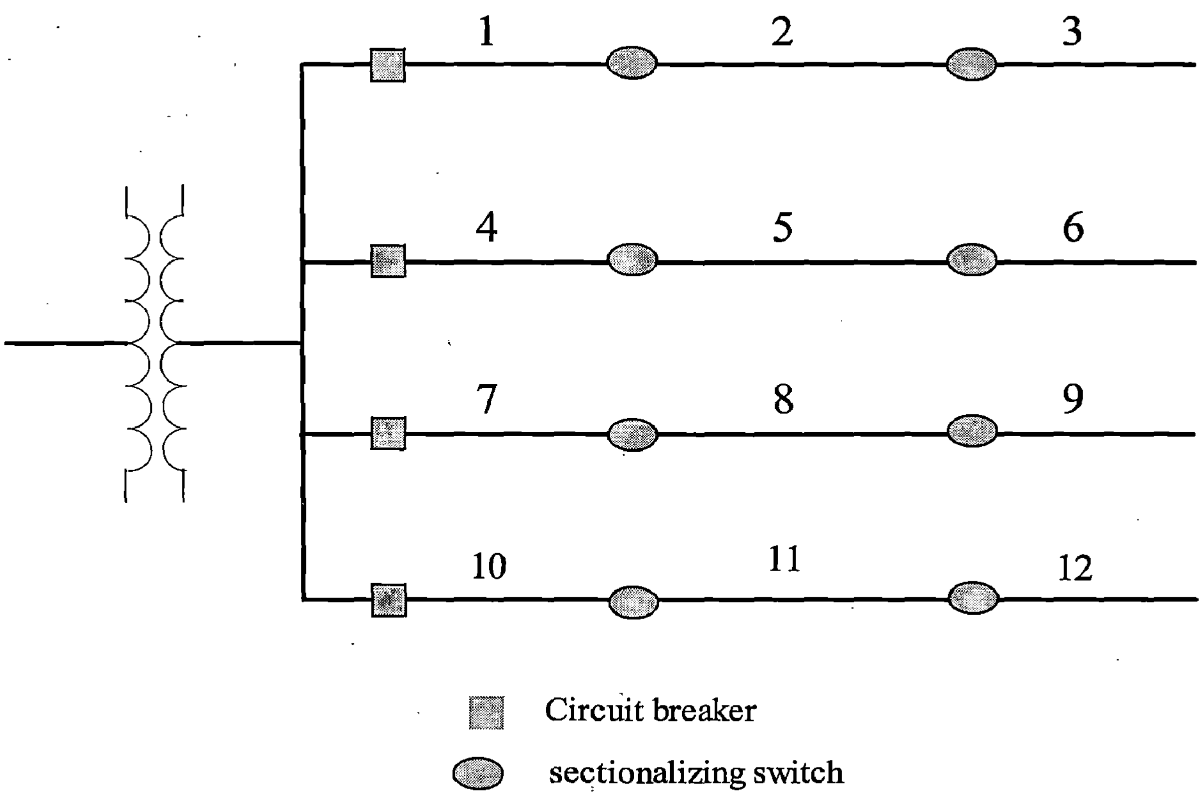


Figure 5.1 the distribution system

A delayed exponential model has been proposed to characterize the aggregate load during cold load pickup [14]. Figure 5.2 shows the variation of the load with time when cold load pickup conditions persist according to this model. Here, $S(t)$ is the load as a function of time, T_{out} is the outage duration, S_U is the undiversified load, S_D is the diversified load, α is the rate of load decay, and Δ is the undiversified load duration. Following an outage, the section load reaches the undiversified maximum value S_U for duration Δ. Thereafter, the load decays exponentially towards the diversified load S_D, at a rate α.

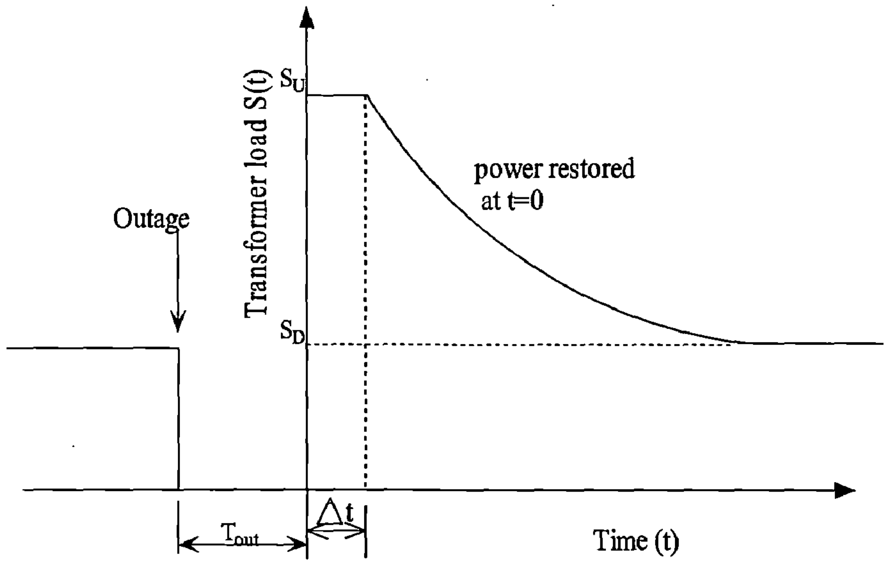


Figure 5.2 model of Cold load pickup

Table 5.1: Load of the network

S l no	Section Number	Diversified Load (MVA)	Undiversified Load (MVA)
1	1	2.5	7.5
2	2	2.5	4.5
3	3	2.0	3.0
4	4	1.5	6.0
5	5	2.5	5.6
6	6	2.0	6.5
7	7	2.5	4.0
8	8	2.0	9.0
9	9	3.0	6.0
10	10	3.0	6.0
11	11	1.5	4.8
12	12	2.0	6.0

The restoration time of the i^{th} section to be restored, $T_{[i]}$, can be calculated using the following equation [1]

$$T_{[i]} = \left(\frac{S_{MT} - S_{U[i]} - \sum_{l \in R} S_{D[i]}}{\sum_{l \in R} \left(S_{U[l]} - S_{D[l]} \right) e^{\alpha \left(T_{[l]} + \Delta \right)}} \right) \qquad \text{..............} (5.1)$$

Where

S_{MT} is the maximum allowable transformer loading. The quantities $S_{U[i]}$ and $S_{D[i]}$ are the undiversified and diversified loads respectively of this section. The number shown within square brackets is an index representing the order of restoration, which is not to be confused with the section number. The set R contains all the previously restored sections. The total restoration time is the time required before the last section is restored. It is clearly dependent on the order in which the step-by-step restoration is carried out [1].

For finding the optimal restoration time I have chosen genetic algorithm, this method I have already explained in chapter-3. In this fitness function evaluates the best individuals are selected randomly from the population.

If f_l denotes the fitness of the l^{th} individual, then the probability of selection is given by [1]

$$p_l = f_l / \sum f_l' \qquad \text{..........................} (5.2)$$

It is iteratively assembled by picking and adding individuals from the parent pool stochastically based on fitness, and with replacement. The process is repeated until the intermediate population has $2N$ sequences of sections.

Letting the total restoration time corresponding to the l^{th} individual of a population of sequences, we denote as T_l, its fitness was computed as

$$f_l = \frac{\max_k(T_k) - T_l}{\max_k(T_k) - \min_k(T_k)} \quad \text{.................................... (5.3)}$$

Where

Each T_l is determined by Eq. (5.1). The fitness computed in this manner is scaled to lie between zero and unity [1].

After this cross over and mutation …

As an example, in the sequence parent = (1 4 7 2 8 5 10 9 3 6 11 12), sections 4 and 2 can be swapped to obtain a new offspring (1 2 7 4 8 5 10 9 3 6 11 12). But sections 1 and 9 cannot be swapped as that will result into an invalid sequence of (9 4 7 2 8 5 10 1 3 6 11 12), in which section 2 appears before section 1 and section 9 appears before sections 7 and 8.

Results are shown in chapter-6

5.2 Ant Colony Optimization Algorithms:

5.2.1. Description of the Algorithm

The ant colony approach is a new method of solving combinatorial optimization problems. It is derived from the foraging behavior of ants, cooperates to obtain an optimal path from their nest to a food source. Ant colony algorithms [23, 24] were originally proposed as a method for the traveling salesperson problem, where the problem is also one of determining a minimum distance path.

In each turn of the algorithm, an ant produces a candidate solution for the optimization problem, which in our case is a sequence of sections for restoration. Each ant defines a candidate solution piece-by-piece starting from an empty sequence, probabilistically adding a new section at a time, until an entire sequence is obtained. Although each ant's traversal yields a single solution of the optimization problem, the ants cooperatively compute better solutions with increasing iterations. Therefore, the ant colony approach can be regarded as a search through the solution space of the problem instance. As we will see, the search converges gradually onto regions where potentially good solutions can be found.

The ant's traversal is guided by the pheromone trail. The stronger the pheromone concentration along any path, the more likely an ant is to include that path in defining a solution. However, the ant is guided not solely by pheromones, but by another factor called the desirability. The desirability is computed initially and remains constant throughout the algorithm [1].

5.2.2 Desirability

An ant's traversal is biased to wards picking up more desirable components of the solution. In the present problem, restoring sections with larger undiversified loads allows these loads to assume stable diversified levels at an earlier stage of the restoration. This usually results in quicker overall restoration. Hence, the desirability η_j of picking a section *j* for restoration is simply set to $\eta_j = S_{U_j}$.

5.3. Path Traversal

In each iteration, a new ant, starting from an empty sequence, assembles a full sequence, which is a valid solution. Each path that the ant takes towards this solution sequence results in a new section being appended to a partially completed sequence as a new section for restoration. The probability that an ant will select an unrestored section *q* in the set Ready of sections that are ready for restoration as the next section for restoration, following any other section *r*, is equal to the normalized product of the desirability and trail concentration, exponentiated appropriately. It is given by [1],

$$p_{qr} = \frac{(\tau_{qr})^{\gamma}(\eta_q)^{\beta}}{\sum_{q'}(\tau_{q'r})^{\gamma}/(\eta_{q'})^{\beta}} \qquad \text{(5.4)}$$

In the above equation, the exponent's γ and β are two parameters associated with the ant colony algorithm. The variable τ_{qr} is the pheromone concentration along the path from section q to section r. For the very first element that is inserted in to the sequence, the pheromone concentration is simply assumed to be unity [1].

5.4. Pheromone Updating

The process of pheromone deposition is a very important aspect of the algorithm. The pheromones are updated only at the end of each iteration when the ant completely defines a sequence. Furthermore, the increment is inversely related to the quality of the solution generated. For those pairs of sections (q, r) that appear in the sequence that the ant generated, the trail is updated according to the equation below [1]

$$\tau_{qr} = (1-\rho)\tau_{qr} + \rho\Delta\tau_{qr} \qquad \text{.................. (5.5)}$$

Where ρ is the evaporation rate and the quantity $\Delta\tau_{qr}$ is a pheromone intensity increment, which is equal to the following

$$\Delta\tau_{qr} = \frac{Q}{T} \qquad \text{.................. (5.6)}$$

Where T is the total restoration time and Q is one of the parameters associated with the algorithm. For all other pairs of sections, the pheromone concentrations are simply subject to evaporation as [1]

$$\tau_{qr} = (1-\rho)\tau_{qr} \qquad \text{.................. (5.7)}$$

Results are shown in chapter-6.

CHAPTER-6

RESULTS AND DISCUSSIONS

In this I have given only results. I have taken the data (CLPU) from substation in winter as well as in summer. First of all I want show the variations of all parameters. The variation of active power, reactive power, load and current with time are shown below.

6.1 Summer season:

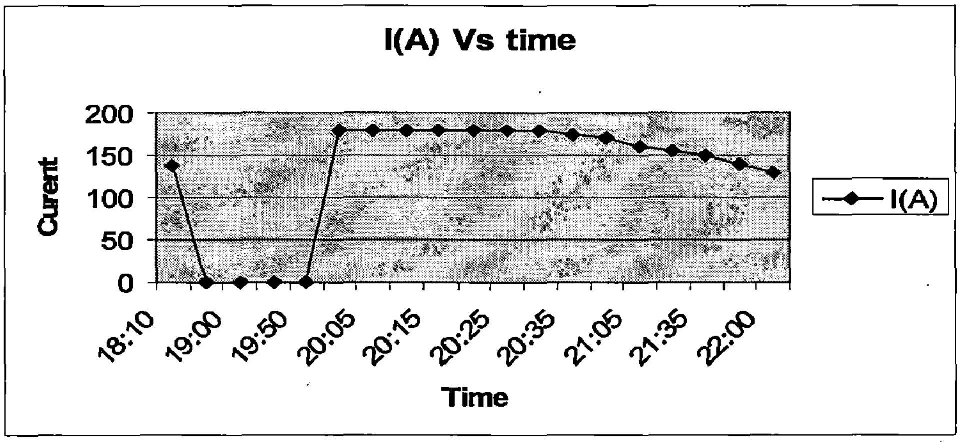


Fig 6.1 Current Vs Time

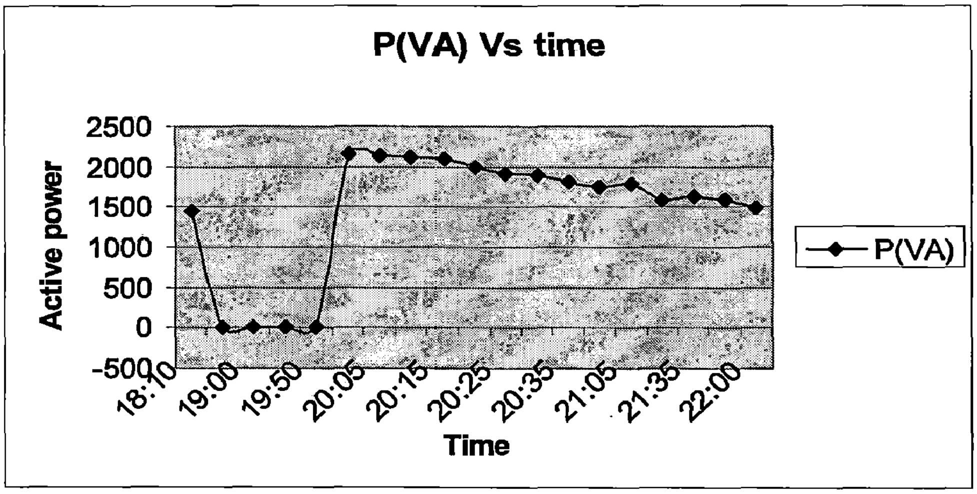


Fig 6.2 Active power vs. Time

Table 6.1: Piran Kaliyar

Date: 4/05/06

S No	Time	I(A)	V(KV)	Temp	P.f	P(VA)	Q(VAr)	S
1	18:10	138	11.0	62	0.86	1437.92	853.21162	1672.0
2	18:30	0	0	-	0.86	0	0	0.0
3	19:00	0	0	-	0.87	0	0	0.0
4	19:30	0	0	-	0.87	0	0	0.0
5	19:50	0	0	-	0.92	0	0	0.0
6	20:00	180	11.7	64	0.90	2106	1019.9824	2340.0
7	20:05	180	11.7	64	0.92	2152.8	917.08896	2340.0
8	20:10	180	11.7	65	0.85	1989	1232.6715	2340.0
9	20:15	180	11.6	65	0.92	2134.4	909.25059	2320.0
10	20:20	180	11.6	66	0.90	2088	1011.2646	2320.0
11	20:25	180	11.6	64	0.87	1917.48	1086.686	2204.0
12	20:30	180	11.5	65	0.87	1900.95	1077.318	2185.0
13	20:35	175	11.3	66	0.87	1818.74	1030.7246	2090.5
14	20:50	170	11.2	65	0.87	1753.92	993.99227	2016.0
15	21:05	160	11.1	64	0.90	1798.2	870.90801	1998.0
16	21:20	155	11.0	65	0.85	1589.5	985.08363	1870.0
17	21:35	150	11.0	66	0.9	1633.5	791.14016	1815.0
18	21:50	145	11.0	65	0.87	1579.05	894.88887	1815.0
19	22:00	145	10.8	64	0.86	1486.08	881.78809	1728.0
20	22:15	145	10.7	62	0.89	1466.08	871.98	1708.25

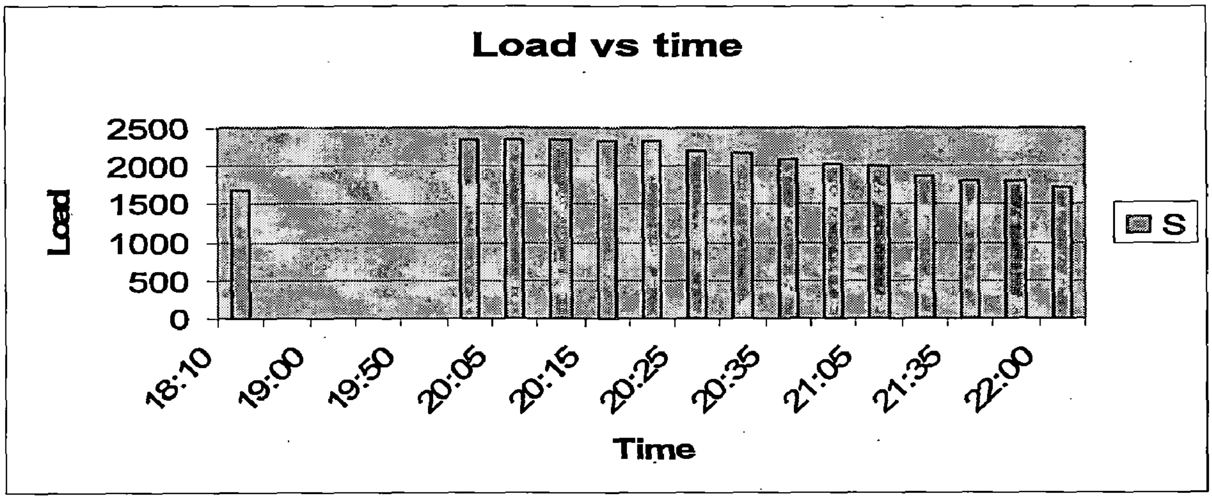


Fig 6.3 Load Vs Time

6.2 Winter season

As compare to the summer season winter season draws more power because of thermostatically-controlled devices such as air-conditioners, heaters, and heat pumps these devices draws 2 to 5 than normal load.

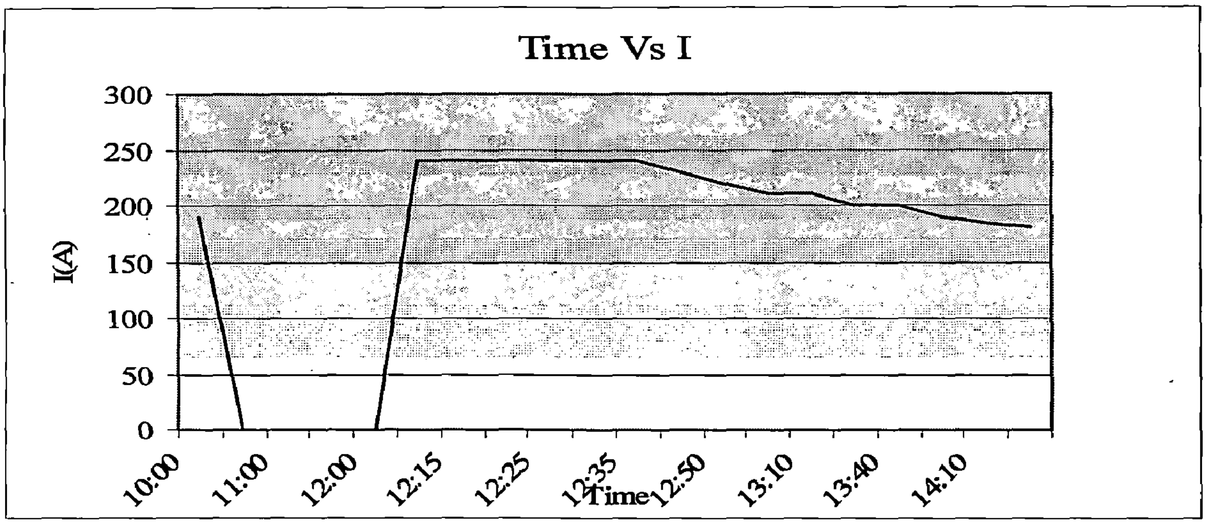


Fig: 6.4 Current Vs Time

Table 6.2: Piran Kaliyar

Date: 07/01/06

S No	Time	I(A)	V(KV)	Temp	P.f	P(VA)	Q(VAr)	S
1	10:00	190	10.8	59	0.88	1805.76	974.646	2052.0
2	10:30	0	0	-	0.88	0	0	0.0
3	11:00	0	0	-	0.87	0	0	0.0
4	11:30	0	0	-	0.89	0	0	0.0
5	12:00	0	0	-	0.89	0	0	0.0
6	12:10	240	11.1	58	0.90	2397.6	1161.2107	2664.0
7	12:15	240	11.1	59	0.90	2397.6	1161.2107	2664.0
8	12:20	240	11.1	60	0.91	2424.24	1104.5164	2664.0
9	12:25	240	11.1	60	0.92	2450.88	1044.0705	2664.0
10	12:30	240	11.1	61	0.94	2504.16	908.88871	2664.0
11	12:35	240	11.1	62	0.92	2450.88	1044.0705	2664.0
12	12:40	230	11.0	62	0.91	2302.3	1048.9589	2530.0
13	12:50	220	11.0	63	0.92	2226.4	948.44243	2420.0
14	12:55	210	10.8	64	0.89	2018.52	1034.1185	2268.0
15	13:10	210	10.8	62	0.9	2041.2	988.59828	2268.0
16	13:25	200	10.8	61	0.91	1965.6	895.55382	2160.0
17	13:40	200	10.8	60	0.89	1922.4	984.87473	2160.0
18	13:55	190	10.8	60	0.88	1805.76	974.646	2052.0
19	14:10	185	10.8	61	0.87	1738.26	985.11734	1998.0
20	14:20	180	10.8	61	0.89	1730.16	886.38726	1944.0

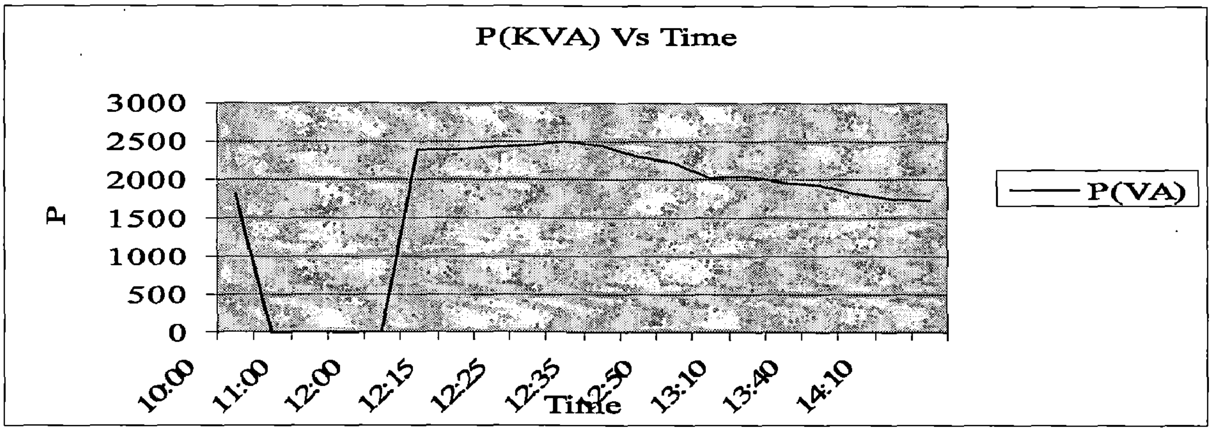


Fig 6.5 Active power vs. Time

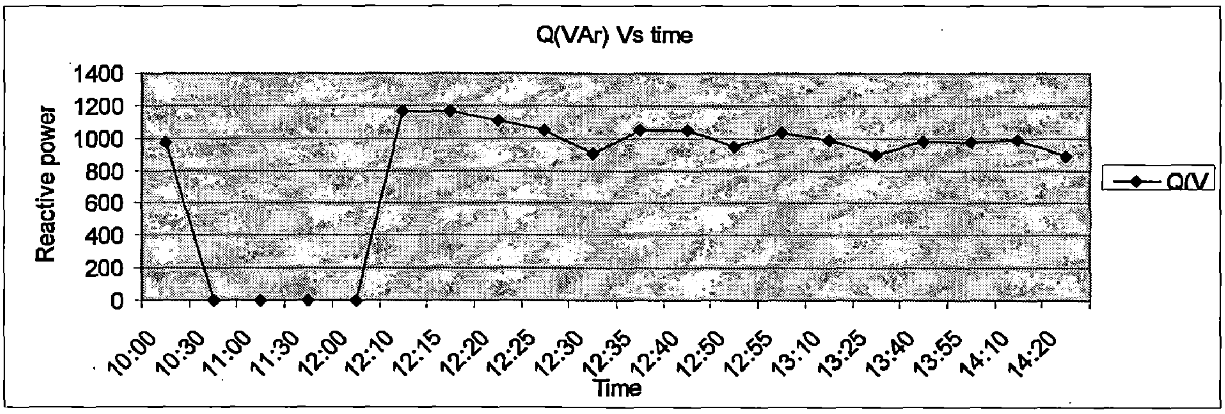


Fig 6.6 Reactive power vs. Time

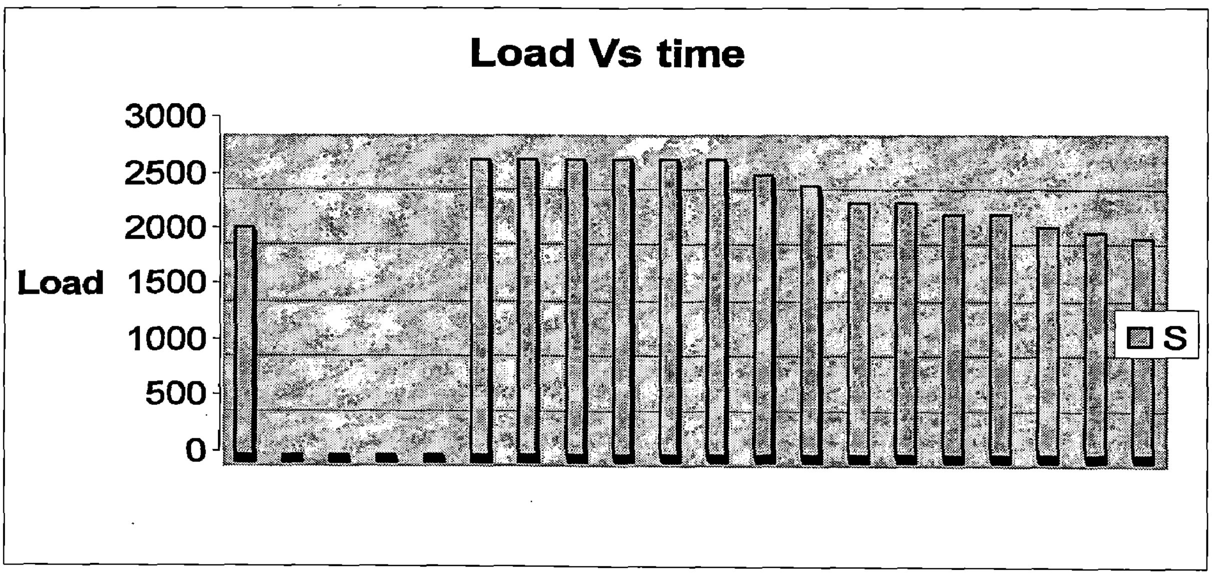


Fig 6.7 Load Vs Time

As per above graphs I concluded that after outage sudden variation is coming because of these thermostatically-controlled devices and it is satisfying with delayed exponential model which is I explained in chapter 4. Expect reactive power reaming all are decreasing exponentially.

6.3 Transformer Size and Loss of Life

In order to find the size and loss of life we need below values:
From the above graph I have chosen one graphs (transformer load), in this graph Diversified, undiversified loads and Δt are 2.8 MVA, 9.3 MVA and 30 mints.

$K_p = 150\%$,

No of transformers = 1

No of feeders = 2 (jadugar road and Piran Kaliyar)

Average no of outges per year (1 per two days) = 0.5

Ambient temperature = 39^0 c

For this data I have been applied optimization technique Genetic Algorithm from this GA I got following results with MATLAB.

From this above data I found that

Size of the transformer (Roorkee substation) = 6 MVA

Number of sectionalizing devices = 0

Transformer Loss of Life (in %) = 0.2376

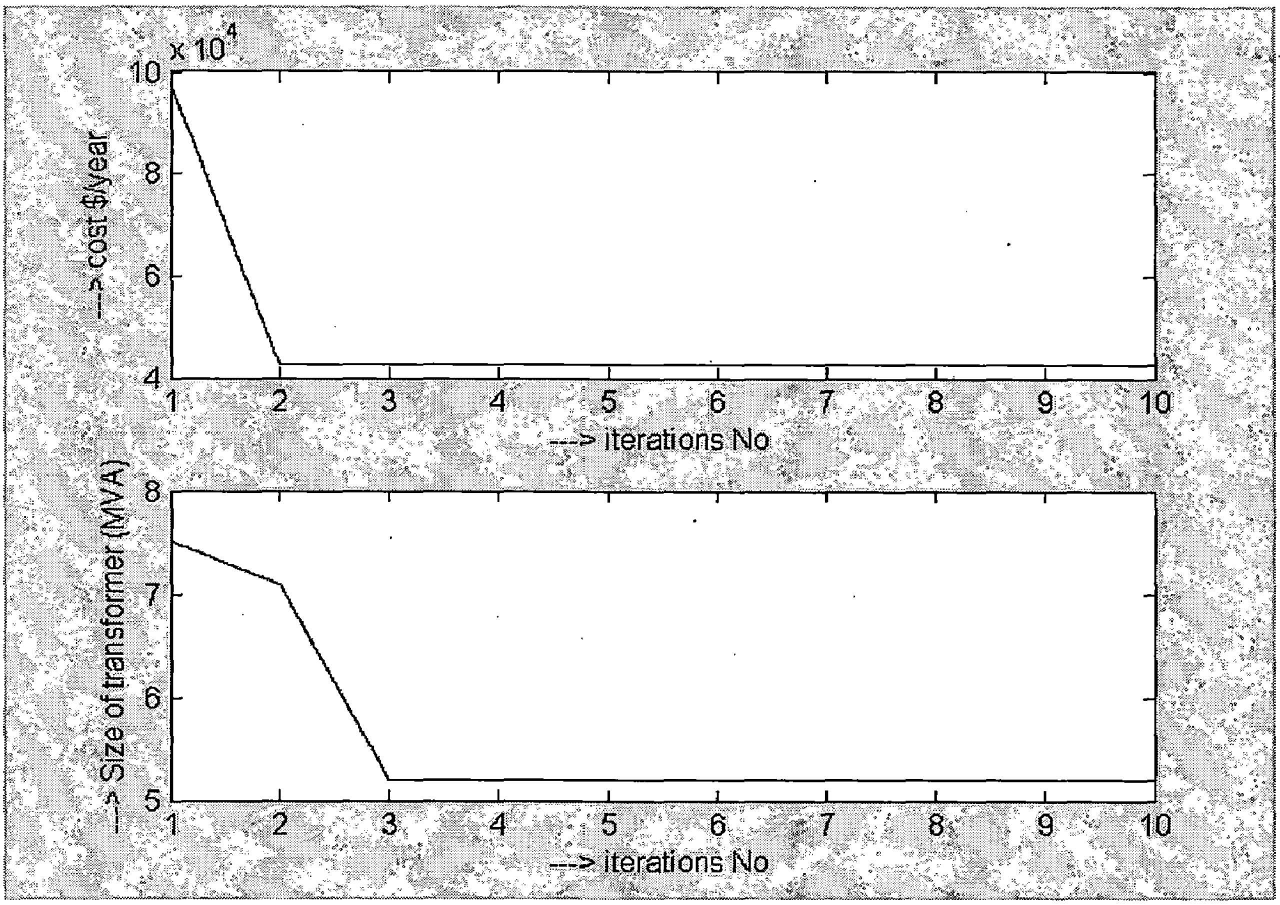


Fig 6.8 Transformer size

Fig 6.9 Cost function

6.4 optimal restoration time of the network

Network is having 4 sections and 12 feeders for this total average minimum restoration time is calculated by using two methods for comparison purpose of methods with MATLAB programming.

In first method (GA) we have two more cases and Table 6.3 shows the diversified and undiversified loads for the distribution system.

Case 1A mild case of cold load pickup and Case 2 is an extreme case of cold load pickup. In Case 1, the transformer maximum loading capacity (S_{MT}) was 1.5 times the rated capacity , the rate of load decay (α) was 1.25 per hour, and the undiversified load duration (Δ) was 0.33 hours. In Case 2, the transformer maximum loading capacity (S_{MT}) was 1.45 times the rated capacity, the rate of load decay (α) was 0.5 per hour, and the undiversified load duration (Δ) was 0.5 hours. The maximum transformer loading was reduced for Case 2 to avoid overheating of the transformer due to extreme conditions. Such extreme situations may not occur very often, but are becoming more possible with loading of transformers increasing gradually

Case 1:

Average minimum restoration time is = 62 mints

Case 2:

Average minimum restoration time is = 260 mints

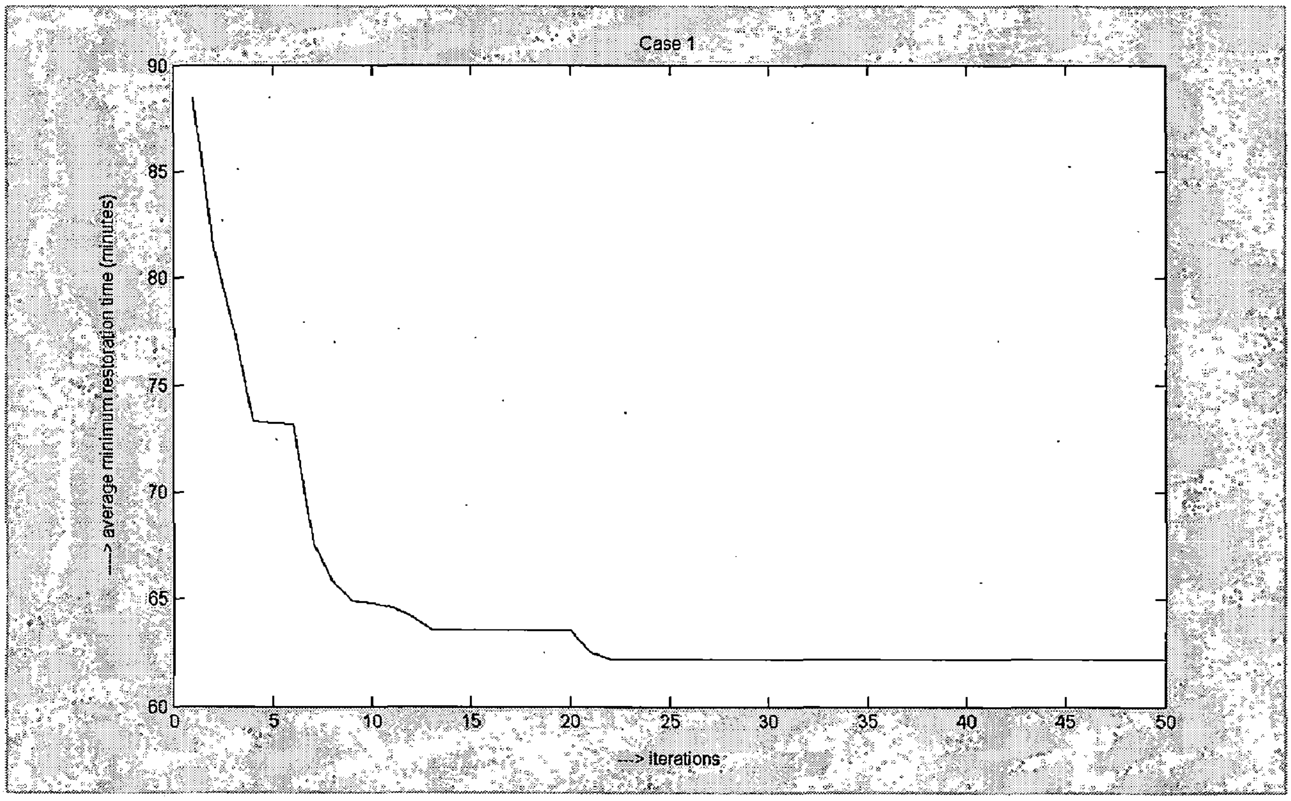


Fig: 6.10 GA case1 restoration time

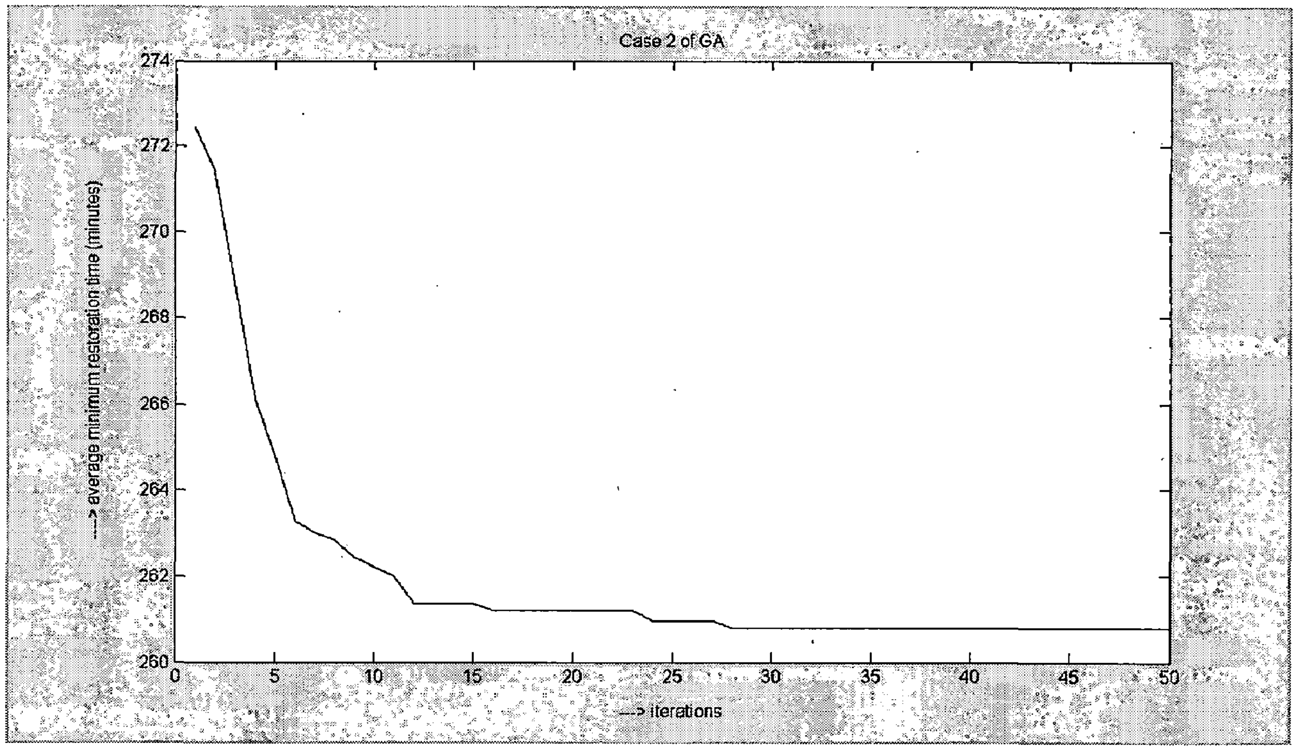


Fig: 6.11 GA case2 restoration time

Ant Colony Optimization:

The pheromone evaporation rate is $\rho = 0.02$,

The exponents were $\gamma = 0.5, \beta = 0.5$,

And $Q = 10^4$ in the ant colony algorithm.

By comparison of the two methods it's observed that GA convergent more faster than ACO

Fig: 6.12 ACO case1 restoration time

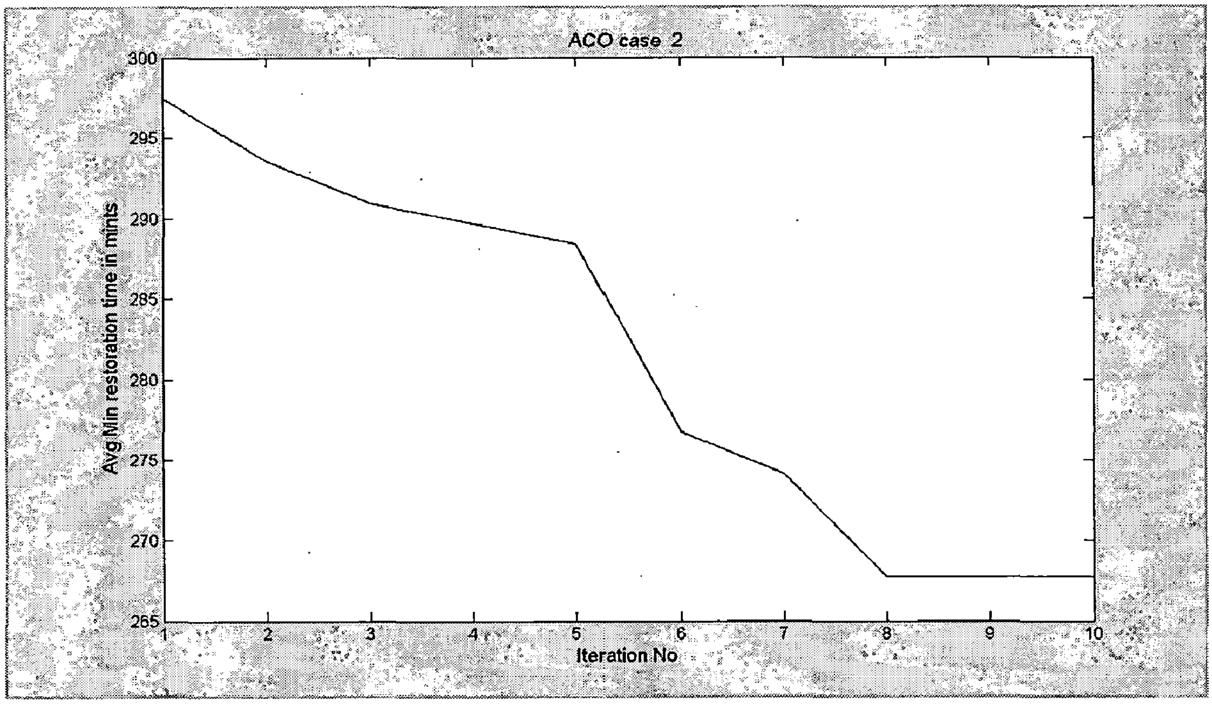


Fig: 6.13 ACO case2 restoration time

CHAPTER-7

Conclusions and Scope of Future Work

The Cold Load Pickup is one of the most severe conditions that a power distribution system faced. This thesis work gives a formulation of an Optimization problem for the design of power distribution system, taking cold load pickup into consideration. A solution was obtained for the optimization problem and the results were compared with the different optimization techniques. By this solution, the distribution substation transformer size, number of sectionalizing switches and transformer Loss of Life is determined. This transformer size minimizes the annual cost function.

Genetic Algorithms and Ant Colony Optimization techniques are used for optimal designing of a distribution system. The optimal restoration time of the network got from these two methods are compared and genetic algorithms are found to be effective among the two.

Results obtained for the system (Roorkee substation), and are compared with the IEEE standards (C57.92.1981). It is observed that as the size of the transformer increases, its cost function decreases gradually (Eg: S=6MVA the cost is 5887.32 and up to S=40MVA its decreasing and further means S=50MVA its increasing and the cost is 2261.28) and vice versa. If the transformer size is further increased, its cost function also increases.

Future scope of work is to reduce the Annual cost of the system for this instead of using sectionalizing switch we use Distribution generators so that we can minimize the cost to some extent.

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Appendix-A

Cost of Transformer

Cost of the transformer increased as decreasing the size of the transformer and we increase size some extent it decreasing if you are increasing further cost of the transformer increased.

Table A.1:

ST,MVA	COST		
	$	$/MVA	$/MVA,YEAR
7.5/8.5/9.5	246000	25894.7	5228.15
12/16/20	350000	17500	3533.25
15/20/25	380000	15200	3068.88
24/32/40	430000	10750	2170.42
30/40/50	560000	11200	2261.28

Table A.2:

S l No	Size (S_T) MVA	Cost (Linear)	Cost (Quadra)
1	6	4861.32	5887.38
2	9	4700	5228.15
3	20	3900	3533.25
4	25	3450	3068.88
5	40	2450	2170.42
6	50	1800	2261.28

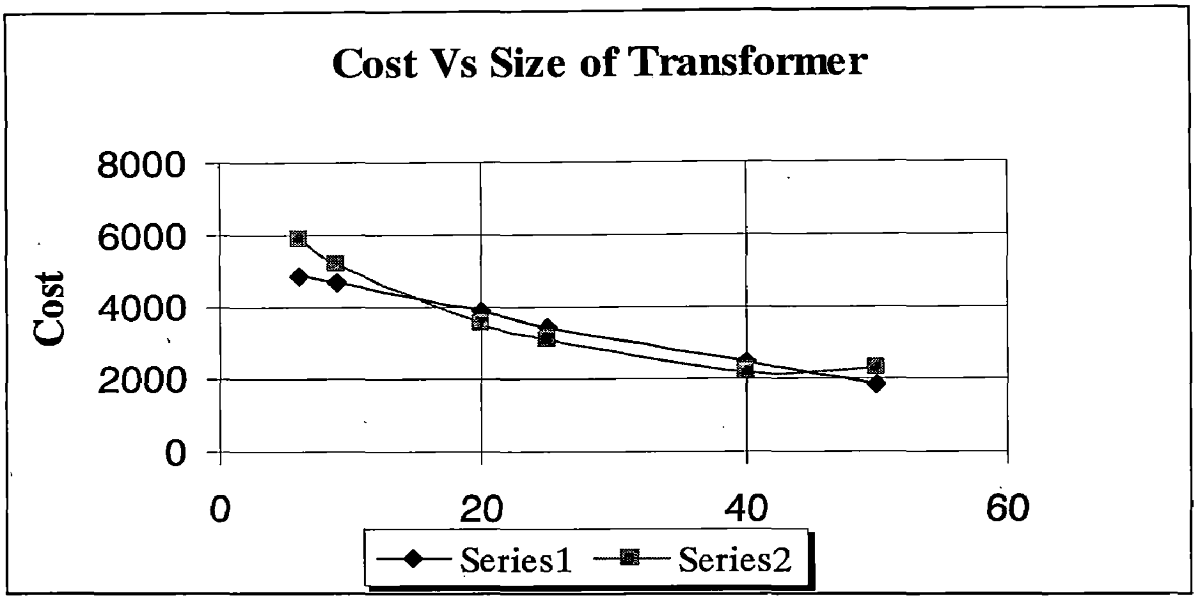
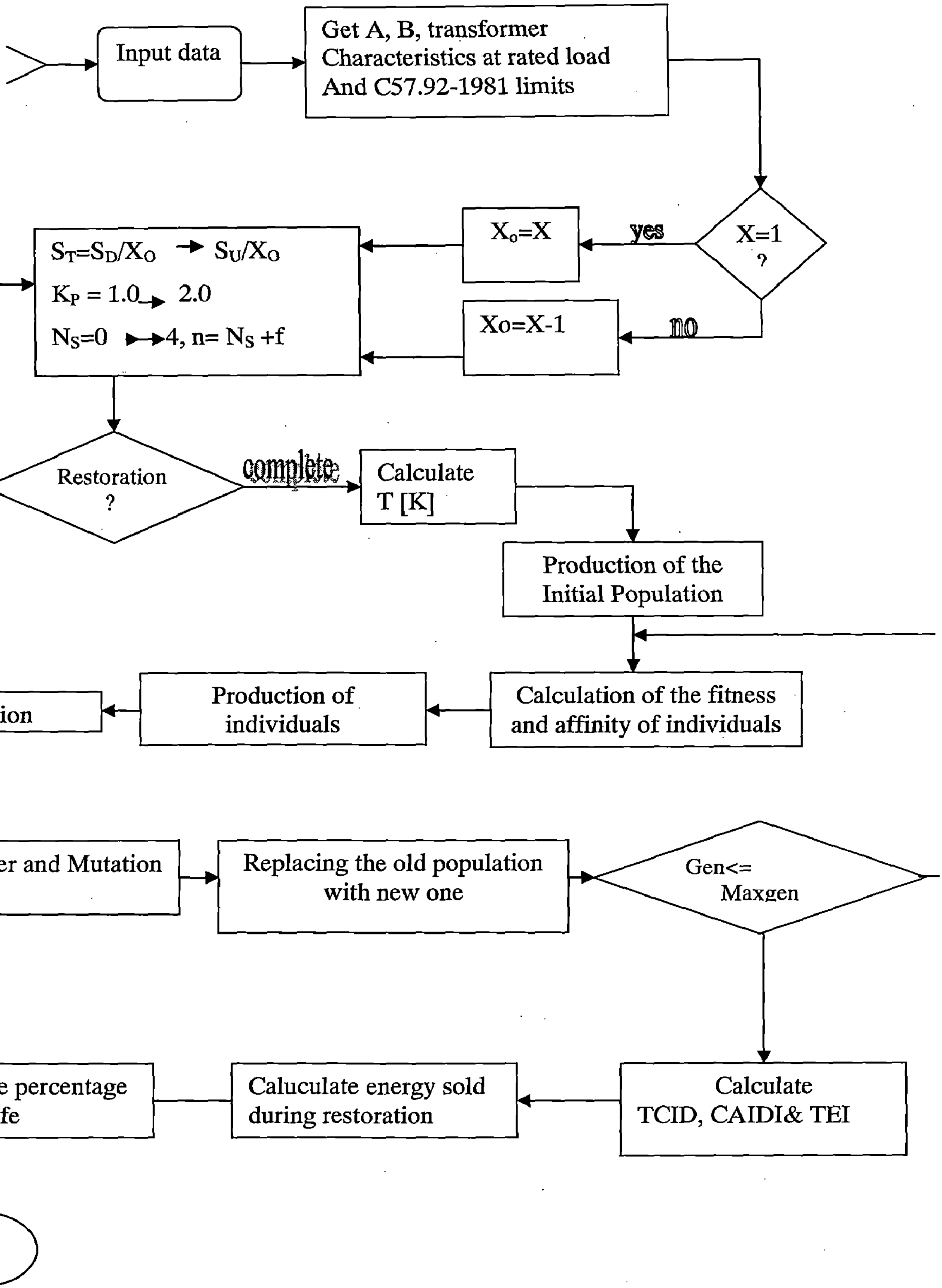


Fig A.1 Transformer least square approximation of data

Flow chart:



Input data
Get A, B, transformer Characteristics at rated load And C57.92-1981 limits
X=1 ?
yes
X_o=X
no
Xo=X-1
$S_T=S_D/X_O \rightarrow S_U/X_O$
$K_P = 1.0 \rightarrow 2.0$
$N_S=0 \rightarrow 4$, n= N_S +f
Partial
Restoration ?
complete
Calculate T [K]
Production of the Initial Population
Calculation of the fitness and affinity of individuals
Production of individuals
Selection
Crossover and Mutation
Replacing the old population with new one
Gen<= Maxgen
Calculate TCID, CAIDI& TEI
Caluculate energy sold during restoration
Calculate percentage loss of life
End