Analysis of Electric Field Distribution Along Insulator Surface by Genetic Algorithms

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ABSTRACT

Insulators are essential parts of power systems by means of electrical insulation and mechanical connections. In order to design a cost-effective insulation system, the stress distribution along the insulators should be uniform with keeping the electric field as minimum as possible. Since the electric field heavily depends on geometric shape, to have a uniform stress distribution an optimal contour design for insulators should be used. Using optimal geometries, insulation characteristics of an electrode system can be improved.

In this study, Genetic Algorithm (GA) method is used for analyzing stress distribution along a support insulator surface. Genetic algorithm can be applied to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear. In this study, electric field distribution is determined by the software COMSOL 4.3 of finite element method and a fitness function is generated to be optimized. GA searches for the optimum solution for insulator geometry having a uniform and as minimum as possible electric field distribution along the surface.

Keywords: Contour Optimization Of Insulator, Genetic Algorithm, Finite Element Method

ÖZ

İzolatörler, güç sistemlerinin elektriksel yalıtım ve meknik dayanım bakımından vaz geçilmez bir parçasıdır. Etkin ve ekonomik bir sistem tasarlanabilmesi için, izolatör yüzeyindeki zorlanmanın düzgün ve mümkün olduğunca küçük olması gerekmektedir. Elektrik alan, geometrik şekle çok bağlı olduğu için, düzgün alan dağılımı için, izolatör biçimi optimum olacak şekilde tasarlanmalıdır. Optimum geometri kullanarak, bir elektrot sisteminde yalıtım karakteristikleri geliştirilebilir.

Bu çalışmada, bir mesnet izolatörü yüzeyindeki alandağılımını incelemek için Genetik Algoritma (GA) kullanılmıştır. Genetic algoritma, amaç fonksiyoları türevi alınamayan, stokastik veya doğrusal olmayan gibi standart opmizasyon yöntemlerine uygun olmayan çeşitli problemlerin çözümün euygulanabilir. Bu çalışmada elektrik alan dağılımı, Sonlu elemanlar çözümü yapan COMSOL 4.3 programı ile hesaplanmıştır ve optimize edilecek amaç fonksiyonu belirlenmiştir. GA, izolatör yüzeyinde düzgün ve olabildiğince küçük alan dağılımı elde edecek şekilde, optimum izolatör geometrisini arar.

Anahtar Kelimeler: İzolatör Biçim Optimizasyonu, Genetik Algoritma, Sonlu Elemanlar Yontemi.

To my family

For their supports, and encouragements

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B	Random number on the interval
D	Electrical flux density
E	Electrical stress
e	Element
F	Total electrical energy
F_i	Electrical energy in node i
H	Height of the insulator
h_s	Height of screw
J_{cond}	Conduction current
J_{cap}	Capacitive current
M	Mass of an electron
P_{lo}	Lower limits for the design parameters
P_{hi}	Upper limits for the design parameters
P_{norm}	Normalized value of variable
P_{new}	New variable values
P_{mn}	N^{th} variable in the mother chromosome
P_{dn}	N^{th} variable in the father chromosome
$p\&q$	Two mutually orthogonal directions tangential
r_s	Radius of screw
r_M	r-coordinates of the top point
$[S_i]$	Stiffness matrix
U	Electron density
V	Potential
V_i	Potential in node i
$[V_i]$	Nodal potential matrix
W	Weight
x	Distance of the point from the cathode
μ_E	Tangential field
ρ_v	Free charge density
σ	Time derivative
$\sum_e$	Summation of contributions from all elements
∇	Nabla
σ_E	Standard deviation
Ω	Volume
∂	Partial differential
ω	Radian frequency

Chapter 1

INTRODUCTION

1.1 Introduction

Recently, with acceleration of technological and industrial developments, application of alternating current system with high quality in modern societies has been significantly increased. Telecommunication and computer network, post and bank nets, railways, hospital security systems and all industrial sections which have alternative performance are just part of departments who need reliable power supply. Consequently, by this development, more electrical energy should be transferred for daily act from power source to the consumers. Simultaneously insurance of electrical energy transfer should be increased. Actually, the long distances between power source and consumer, force to use high voltage level for transferring energy to decrease losses, therefore power supply, transmission line maintenance and management is essential [1]. On the other hand, designing a power transmission network without any fault is not possible, in other words fault is inevitable in power transmission lines. Actually the main challenge in transmission system is to reduce the amount of fault during power delivery. These requirements have provided development in high-voltage techniques.

Obviously, technical developments in high voltage include the development in application of high voltage which is used in network connection system, same as conductors, insulators and switching systems. Normally, in high voltage electrodes to discuss about discharge phenomena, the magnitudes of electrical field should be calculated by means of theoretical and experimental research. Occasionally extremely small currents flowing through the insulator between the electrodes in a high voltage system may lead to a discharge. In this case, most effective way is starting research to discover the cause of short circuits and discharge in high voltage system transfer. Insulators have been the most important equipment in high voltage system. Scientists have been trying to find a new fact about insulations by performing expensive experiments.

In high voltage insulation system, main subject is strong effect of electric field on insulator surface, which causes to create micro size crashes and discharges in insulators. Therefore this type of electric field distribution by the time may damage the insulator.

Obviously overhead power lines organization is designed for standard amount of current and voltage. Due to various load conditions in the network, electric field stress in insulators may increase, therefore insulators must show good performance considering electrical discharge. That means, they should tolerate for more than critical voltage level because of over voltage possibility. In this case, for minimizing the insulator surface flashover, uniform tangential electric field distribution is required for insulators. It means, optimum design of insulator is distributing tangential electric field along the insulator surface uniformly. Consequently, along the insulator contour, sharp points have more probability for discharge because of non-uniform electric field distribution [1]. As previously mentioned, good insulator contour design keeps tangential electric field uniform along the contour. Thus, probability of the corona phenomenon along insulator surface is related to percentage of, insulators tangential electric field.

In this study, in order to determine electric field since it is very difficult to calculate analytically, a numerical method is used. The main purpose of geometric characteristics study of insulators is finding the magnitude and distribution of electrical field across the insulators. The selection of suitable insulators has a significant impact on the insulation coordination and consequently, on dielectric strengths, both inside and outside the insulator. This method is used to compare the performance of characteristics for different insulators in existing structures by using Finite Element Method (FEM).

In high voltage technique, in order to obtain a uniform stress distribution, insulator contour should be optimized. Using optimum insulator not only uniform electric field distribution is obtained along the contour surface but also amount of electric field is kept within limits. That improves electrode systems insulation and insulation abilities of high voltages insulators and increase their life period. Therefore, in this study, under genetic algorithm as an optimization method is explained.

Optimization is the process of making something better, this process includes trying variations of an initial concept and using this gained information gained to improve the idea. Thoroughly, optimal solution depends on problem conditions. Thus collecting the initial data of the problem before optimization is necessary.

Most of the time, iterative methods have been used for optimization of insulators contour. In one of the iterative methods, optimum insulator contour is designed by means of linear interpolation. Obviously, iterative method for optimization performed by interpolation calculation changes from problem to problem. Consequently, this method takes long time to perform. In this study, genetic algorithm is used for optimization. The genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the “fitness” therefore finite amount of inputs simultaneously is processed for specific variables.

In the last decade, wide range of research has been carried out by using genetic algorithm. As a result of the research, literature in GA rapidly increased and improved. Genetic algorithm is a multidisciplinary field of research and it has many applications in different fields. Some of the advantages of genetic algorithm which cause an increase of application in this method are its ability in optimization with continuous or discrete variables and not requiring derivative information. GA can simultaneously search from a wide sampling of the cost surface and deals with a large number of variables. This method has ability to optimize variables with extremely complex cost surfaces and provides a list of optimum variables, not just a single solution. Obviously, GA may encode the variables so that the optimization is performed with the encoded variables, and can work with numerically generated data, experimental data, or analytical functions. GA has been used in load forecasting and capacity control and many other subjects in electrical engineering. In high-voltage systems, genetic algorithm is mostly applied for recognition of critical points in insulator which have been partial discharge by means of bypass over-voltage or lightning and it can simulate this points. Additionally optimization of electrodes in high-voltage system is another important application of genetic algorithm.

The main objective of insulator optimization is designing an insulator contour which not only has a uniform tangential electric field distribution along the surface but also cost cheaper to design. In this study, by means of genetic algorithm, optimum design for a support insulator has been achieved in short time.

In this study, electric field calculation has been carried out by finite element method by using commercial software COMSOL 4.3. An objective function is generated using field values for different insulator geometries. The GA searches for the optimum solution for insulator geometry having a uniform electric field distribution along the surface.

This study is divided into three main parts. In the first section, in order to determine an exact electric field magnitude on insulator surface, finite element method has been briefly explained. In the second chapter, using genetic algorithm as optimization tool is discussed. In the third section, a case study is introduced and results of genetic algorithm application are denoted.

Chapter 2

FINITE ELEMENT METHOD

2.1 Numerical analysis of electrical fields in high voltage equipment

The electric field distribution along insulators influences the long and short term performance of the high voltage system [1]. In order to design safe and economic insulation system and put them into use effectively, the electrical field distribution information is essential. In high voltage applications, when there is a fault, the consequences can be very serious and repair of the system can be expensive [1].

High voltage support insulator is only one of many examples which show the importance of technical analysis of designers for distinguishing or revalidating their designs exactly under all forecasted steady-state and transient operating conditions. Insulator and conductor components plays key role in every electrical system [1]. Ageing of the insulators and, consequently, their life-time depends mainly on the magnitudes of electric field they are subjected to. Physical characteristics such as the geometric arrangements and the material of the insulator attribute to the stress distribution. Therefore, material type, geometry and the applied voltage must be taken into account [1].

As new materials are produced and new configurations designed, it is essential to be able to model the insulation system at the design level rather than to rely only on discretion and experience. Modern design analysis is based on numerical methods, several of which are available to the designer because of the complexity of geometry causes analytical calculations to be difficult to perform. The question is which one suggests the best abilities in terms of speed of analysis, flexibility of modeling and range of investigative options. In this section, a brief review on the electric field distribution of insulators and the related issues is offered [1].

2.2 Comparative summary

There are number of numerical methods for analyzing the electric field distribution along surface of an insulator. Some of them are:

- Finite difference method
- Finite element method
- Charge simulation method
- Surface charge simulation method

First two methods are category in domain methods and second two are in boundary methods [2]. All of these techniques in numerical methods have their advantages and disadvantages; choosing among them is a complicated procedure. Some of these may not be easily applied for slanted and curved surfaces, nodal distribution might be inefficient or they may not be good in handling non-linear materials. It is not so much possible to be certain in deciding which method is the best; different establishments may arise with different conclusions according to the problem. However, history has proved that, a flexible design method, the Finite Element Method is a good choice to the needs of designers. The Finite Element Method is well suited to non-linear model problems and the tender form of the resulting matrix makes it readily adaptable for an efficient solution.

2.3 The finite element method

The Finite Element Method was initially used in the aeronautical and civil engineering industries and improved extensively by Zienkiewicz and Taylor [3] in the late 1950s and early 1960s. It was the late 1960s before the method entered into the electrical engineering industry, but it has been continually developed since.

The main idea of finite element method is breaking the problem down into large number of regions; each region has a simple geometry. By breaking down the problem domain into a number of small elements, the problem is transformed from a complex problem into big, but easier to solve problem. This procedure is discretization. After discretization, an approximate solution is carried out for the field amount in each region. Figure 2.1, is an example of two dimensional axi-symmetrical finite element meshes.

By appropriate selection of elements, complicated geometries can be solved easily and each element can have different physical exclusivities, which can be non-linear (i.e. field dependent). Transforming the ruling partial differential equations into an energy form, an algebraic expression is created for the potential at each node through the inexistence of the energy function. An equation is formed at the nodes on the surfaces of all regions and results in an unsymmetrical matrix. However, the latter results in a very large unsymmetrical matrix to be inverted, so limiting of the complexity of the problem that can be solved. Although a two-dimensional problem is shown in Figure 2.1, the method is similarly adaptable to three-dimensional situations. In this case, the product of the mesh with separate elements is more complex and consequently the solution is time consuming.

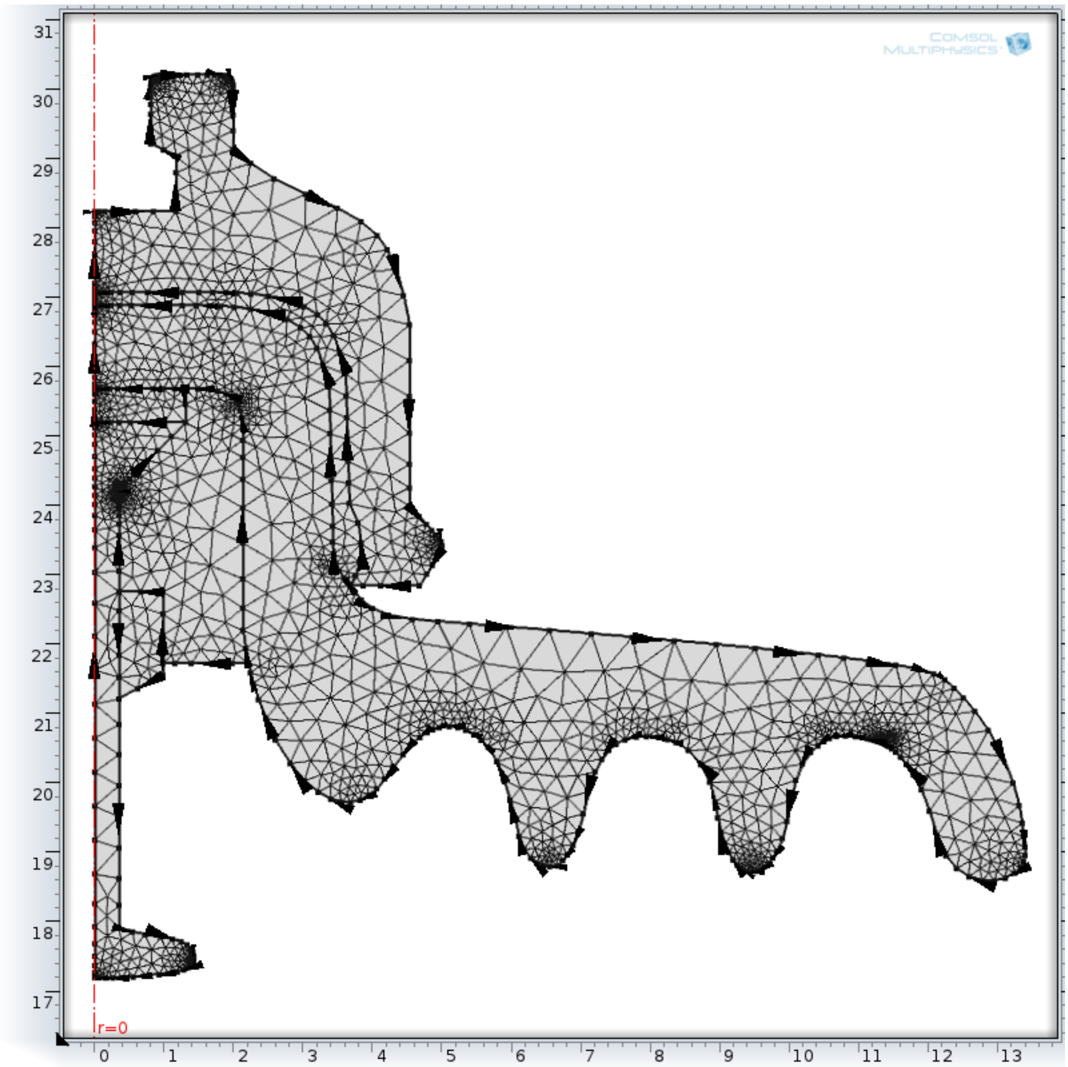

Figure 2.1: Example of a Finite-Element Mesh

The numerical equations are formed from the application of Green's theorem to the partial differential equations that describe the field distribution within the region interested.

2.4 Formulation of the finite-element equations in two and three dimensions

2.4.1 Introduction

The finite element method converts a problem of complicated form in a continuous region into one in which the region is subdivided into a large number of simple regions, known as elements. Each element has vertices. Therefore Solution is obtained for the potential at the nodes that lay the vertices of the element. It is obvious that complicated geometries can be represented well, and each element can have different exclusivities. In order to receive the field distribution in a specified space, a formulation is received through an approach such as the Galerkin Method [4] or directly through a function derived from the stored electrical energy of the region under attention. This function is related to the potential of nodes. Elements have been defined and then integrated over all elements associated with the node interested. Finally it has been given an assumed polynomial variation of potential over the element. Therefore an equation is formed at each node. As result in large set of simultaneous equations that replaces the ruling partial differential equation. To show the process, the method is applied to an electrostatic field problem.

The partial differential equation that describes the voltage potential distribution within any given region is derived as follows:

$$\nabla \cdot \boldsymbol{D} = \rho_{v} \tag{2.1}$$

Where $\boldsymbol{D}$ is electrical flux density, ρ_v is free charge density, and since $\boldsymbol{D}=\varepsilon_0\varepsilon_r\boldsymbol{E}$ then (2.1) becomes:

$$\nabla \cdot (\varepsilon_0 \varepsilon_r \boldsymbol{E}) = \rho_v \tag{2.2}$$

Where $\boldsymbol{E}$ is electrical stress, ε_0 is space permittivity 8.85419 $\times 10^{-12}$ F/m, and ε_r is relative permittivity. To formulate in terms of the electric potential, Vcan be written in terms of $\boldsymbol{E}$:

$$-\nabla V = \boldsymbol{E} \tag{2.3}$$

Substituting this in (2.2) results in the following equation:

$$\nabla \cdot \{\varepsilon_0 \varepsilon_r (-\nabla V)\} = \rho_v \tag{2.4}$$

(2.4) can be rewritten for a homogeneous region as:

$$\nabla \cdot \nabla V = -\frac{\rho_v}{\varepsilon_0 \varepsilon_r} \tag{2.5}$$

(2.5) is called Poisson's equation and applies to a homogeneous medium. If ρ_v is zero, the equation reduces to Laplace's equation for homogeneous media. Thisis shown in (2.6):

$$\frac{\partial^2 \mathrm{V}}{\partial \mathrm{x}^2} + \frac{\partial^2 \mathrm{V}}{\partial \mathrm{y}^2} + \frac{\partial^2 \mathrm{V}}{\partial \mathrm{z}^2} = 0 \tag{2.6}$$

(2.6) is the partial differential equation that describes the voltage potential distribution in high voltage situations where the medium is homogeneous and the charge density is zero.

Using (2.6) in a finite element formulation requires the equation to be transformed into an energy function form that relates directly to the electrical energy of the system. Too many ways are possible for formulating the function equation. A variation method, which is based on Euler's Theorem can be used for forming the energy function [5]. Unfortunately, it is sometimes impossible to recognize the function from it, and it is not usually used. However, Euler's equation can be used to draft the credit of the function since the result returns to the original partial differential form.

The famous method is the energy-related function which can be written directly from electrical stored energy considerations. This method is, more conforming for the engineering rather than a hard mathematical method approximate.

A third method is performed by weighted and this method known as the Galerkin method. The Galerkin method starts by considering that a trial solution potential exists at each node. Interpolation of this set of potentials into the ruling equation will lead to a residual at each node. The equation will not be perfectly satisfied and in general, the trial values will not be correct. It is obvious that an approximate solution can be achieved by adjusting the potentials to minimize the sum of the remains at all the nodes. This method is sometimes called the collocation method. However, a better solution can be achieved by introducing weighting functions at each node to try to force the sum of the local residual errors to zero over the whole domain. This method is described as the weighted residual method. Where the weighting functions used is the chosen shape functions for the discredited region, the method becomes the Galerkin method.

The total electrical energy in a system of volumeΩ may be written as:

$$F = \frac{1}{2}\int_{\Omega} \boldsymbol{D}.\boldsymbol{E}\ \mathrm{d}\Omega \tag{2.7}$$

$$F = \int_{\Omega} \frac{1}{2}\varepsilon_0\varepsilon_r \boldsymbol{E}^2\ \mathrm{d}\Omega \tag{2.8}$$

If it is assumed that the permittivity is constant within the region concerned, then (2.8) may be used to write the energy as:

$$F = \int_{\Omega} \frac{\varepsilon_0\varepsilon_r}{2}\left[\frac{\partial V^2}{\partial \mathrm{x}} + \frac{\partial V^2}{\partial \mathrm{y}} + \frac{\partial V^2}{\partial \mathrm{z}}\right]^2 \mathrm{dxdydz} \tag{2.9}$$

It is obvious that this is the function, when differentiated with respect to V and equated to zero, gives a distribution of V that satisfies the ruling partial differential equation. Physically, the process equals to minimizing the supplied electrical energy i.e. the potential energy of the system for the imposed boundary conditions. The differentiation is most easily carried out on the discredited system, and this will be shown in relation to the two-dimensional case.

For element e (2.10) can be written.

$$\mathrm{Fe} = \frac{\varepsilon_0\varepsilon_r}{2}\int_{e}[(\frac{\partial \mathrm{V}}{\partial \mathrm{x}})^2 + (\frac{\partial \mathrm{V}}{\partial \mathrm{y}})^2]\mathrm{dxdy} \tag{2.10}$$

where suffix e indicates integration over an element.

Hence, the contribution to the rate of changes of F with V from the variation of potential of node i in element e is only:

$$x_e = \frac{\partial F_e}{\partial v_i} = \frac{\varepsilon_0 \varepsilon_r}{2} \int_e \frac{\partial}{\partial v_i} [(\frac{\partial V}{\partial x})^2 + (\frac{\partial V}{\partial y})^2] dxdy \tag{2.11}$$

$$x_e = \frac{\varepsilon_0 \varepsilon_r}{2} \int_e [2 \frac{\partial V}{\partial x} \frac{\partial}{\partial v_i} (\frac{\partial V}{\partial x}) + 2 \frac{\partial V}{\partial y} \frac{\partial}{\partial v_i} (\frac{\partial V}{\partial y})] dxdy \tag{2.12}$$

2.4.2 Numerical representation

To solve high voltage problems using the finite-element method requires (2.12) to be equated to zero. To represent the problem numerically, the problem region is separated into elements and (2.12) is applied at the nodes forming the element vertices. The variation of the potential over the elemental shape has then to be approximated by a polynomial distribution. The order of the chosen polynomial dictates the type of element used, for example a linear distribution would only require a simple triangular element. For higher order shape functions, the number of nodes describing the element must be capable of defining the order used, a second-class shape function over a triangular element requires nodes at the middle of each element side [6]. There will be contributions to the rate of change of the region functional χ with respect to the potential $V_i$at node i from all the elements connected to$i$. In the case shown in Figure 2.2, there will be contributions from elements 1 to 6. Hence, generally, the contribution to $\partial F/\partial V$ from a change in V_i is:

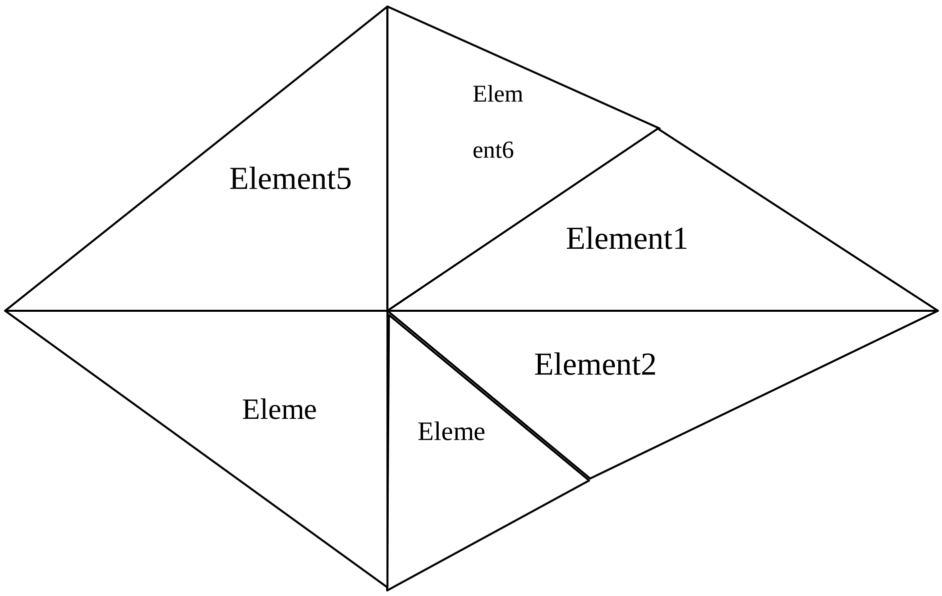

Figure 2.2: Elements Associated with Node [1].

$$\frac{\partial F}{\partial V_i} = \sum_e \frac{\partial F_e}{\partial V_i} \tag{2.13}$$

Where $\sum_e$ represents the summation of contributions from all elements associated with, all the elements connected to node i.

When these derivatives are equated to zero, a group of simultaneous equations is formed. The equation system can be written in matrix form as:

$$[S_t].\{V_i\} = 0 \tag{2.14}$$

Where $[S_t]$ is a square matrix known as the stiffness matrix and is formed from the geometric coordinates of the nodes defining the elements and the material properties. V_i is a column matrix containing all the nodal potentials. The coefficient stiffness matrix will be sparse, it contains many zeros.

It is observed that any node is only coupled to the nodes directly connected to it by an element's edge. Some of the nodes included in the equations fall on boundaries, and their potentials may be known, or some other boundary condition may apply.

2.5 Directional permittivity

In high voltage equipment, there is a considerable amount of insulating material used for support purposes and, in some cases; these structures can have permittivity that depend upon the method of construction [7].

To model directional permittivity, the function equation is modified simply by relating the directional permittivity to the suitable coordinate as shown in the following equation:

$$F = \int_{\Omega} \frac{\varepsilon_0}{2} \left[\varepsilon_x \left(\frac{\partial v}{\partial x}\right)^2 + \varepsilon_y \left(\frac{\partial v}{\partial y}\right)^2 + \varepsilon_z \left(\frac{\partial v}{\partial z}\right)^2 \right] dxdydz \tag{2.15}$$

Chapter 3

GENETIC ALGORITHM

3.1 Introduction to optimization

Optimization is the process of making something better. Scientists create a method and the method has been improved by optimizing procedures. Optimization includes testing variations on first model and using data which is caught form calculation, and improve the method. A computer is the best tool for optimize if and only if the variable affecting the method can be transformed into electronic format. Actually, optimization is the process of adjusting the inputs or characteristics of a device, a mathematical process, or an experiment to find the minimum or maximum output or result (Figure 3.1). The input consists of variables and the process or function known as the cost function, objective function or fitness function; and the output is the cost or fitness. If the process is an experiment, then the variables are physical inputs of the experiment.

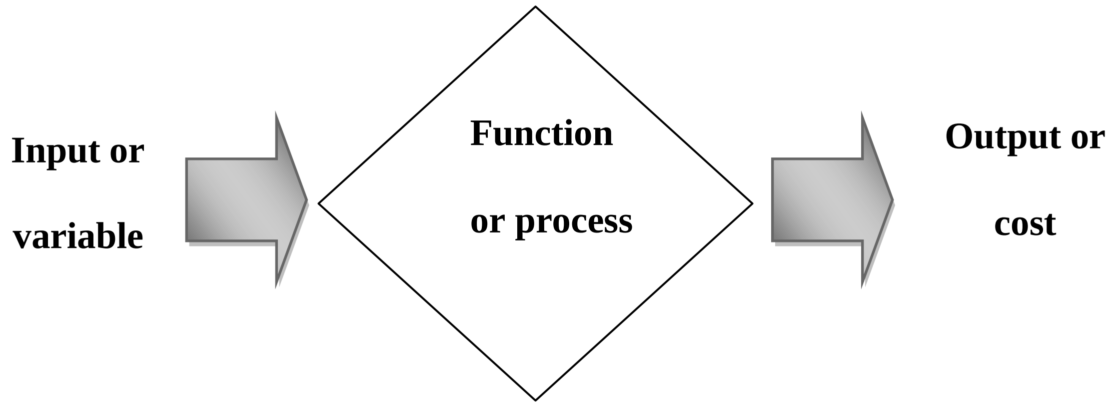

Figure 3.1: Optimization Procedure [20].

Veritably, optimization is a mathematical tool that searches for the best solution. The term “best solution” implies that there is more than one solution and the solutions are not identical. The definition of best depends on the problem at hand, its method of solution, and the tolerances allowed.

3.2 What is the Genetic Algorithm?

The genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the “fitness”.

Genetic algorithm is one of the recent innovations in computational algorithms which have a potential of improvement in artificial intelligence. GA is inspired by the nature and a new theorem to solve problems is developed. A GA mimics the natural evolution, it is based on the principle of survival of the fittest in a population which in nature, the entire cell element which tries to survive, and the information of how to save its life method was hacked into the chromosomes, so that, even for a 1000 years, the information still remains.

The evolutionary algorithms were born in 1960 during the research conducted by I-Rechenberg and they are named “Evolution Techniques”. After that, genetic algorithms were improved by John Holland between 1960s and 1970s years and in the end one of his students make it popular, David Goldberg. He could solve gas-pipeline transmission control problems for his paper (Goldberg, 1989). Actually He was improving a theoretical basis for GAs from his schema theorem. De Jong in

1975 represented the benefit of the GA for function optimization and the first concerted effort have been made to catch the optimized GA parameters. Goldberg has used the GA the most with his successful applications and excellent book (1989). Since then; many versions of evolutionary programming have been tried with varying degrees of success.

3.3 Some concepts in Genetic Algorithm

Body of all living creatures is composed of cells. In all cells, there are chromosomes, and each of the chromosomes includes same DNA blocks. Actually in each gene there is a special protein which encoding is performed on it. Therefore, each gene loads one specific. For example; eye color gene. Obviously, difference between living creatures in nature is related to the difference between their chromosomes.

In reproduction process, first step is crossover. In this step, parents product new genes in several ways. Then, new product genes mutate. Actually, mutation in genes means, changing the element of DNAs. Indeed, when parents copy their genes in reproduction, mutation occurs. Another key word in GA is which means how much living creature has successful in its life. In other words it means how much living creature can be successes in reproduction [9]. Obviously, living creatures should be compatible with its environment to find success in reproduction.

Therefore this kind of changes is named living creature gene as an evolution, and observe all evolution problems by means of genetic theorem, and solve them with genetic algorithm.

For solving a problem by means of genetic algorithm, finding the best way to show the problem solutions is initial step. Veritably in genetic algorithm each of solution is one of genetic algorithms' chromosomes.

Solving an optimization problem is indeed trying to find the best and optimal solution for that problem. In fact, the space where the solutions exist is the research space. Each point in the searching space is one of the solutions. Each solution is evaluated by its suitability. Therefore, solving a problem means finding a minimum or maximum value for that problem. Indeed one of the problems in optimization is complication of searching progress, how to start searching the best solution is unknown. Genetic algorithm has an advantage by this manner which helps to search in a definitive area, and this area is called as searching space.

Genetic algorithm starts with company of solution which is showed by chromosomes and named genetic population. Solutions are selected among genetic population and they are used for generating another population. The advantage of this method is trying to make a better population in every next generation. Obviously genetic population includes chromosomes and the population is limited. Actually chromosome selecting procedure is carried out in population according to chromosome's quality because of the optimization purpose in the next population. Chromosomes which have better quality have more chance for reproduction, thus they have more chance to stay in next population. Those chromosomes are called "elite" in genetic algorithm. Thoroughly this action will be repeated till the stopping conditions are fulfilled.

3.4 Fitness function

Generally in chromosomes, fitness plays a big role for the continuity of their life. It means chromosomes which have better quality have more chance to survive and reproduce. Therefore, to determine which solution (or chromosome) is better than others, fitness function is introduced. This function takes the solutions (chromosomes) one by one and processes them to give a value as an output. This value shows the fitness of that chromosome as a solution.

In genetic algorithm there are too many performances to produce next generation from previous population of and they are called genetic operators. Usually, in genetic algorithms initial population chromosomes are generated randomly. Chromosomes with higher quality are selected according their fitness from initial population. Then genetic operations are carried out and transferred to the next generation. Chromosomes are represented by encoding. One of the popular methods in encoding the chromosomes is binary encoding method. In this method, all chromosomes are denoted by bits. For instance;

11011001001110110 chromosomes bits

In this method, all of the chromosomes have their own binary code which is related to one of the solutions. One of the initial questions in this case is how chromosomes are built and how they are encoded and how we can choose their encoding type.

Another question is how to select the parents for the mating process. This process can be done in any way but the main objective is to find the best parent to reach to the best offspring. Additionally, producing the new population may cause to loss of the best chromosome. According to this issue Elitism technique is introduced which copies at least one chromosome or in another words, solution, to next generation without any change, thus the best solution can stay till the end of the progress. Indeed by this method in genetic algorithm at least one chromosome is selected from initial population and transferred to next generation.

3.5 Crossover

In this process, chromosomes are chosen as parents to produce a new offspring. One of the simplest ways to do crossover is selecting crossover point in the chromosomes randomly. It means, crossover points in parents' chromosomes are selected randomly and the first parents' chromosome data till crossover point is integrated by second parents' chromosome data after crossover point and create a new offspring. An example for this procedure is given in below:

Chromosome 1	11011001 / 00110110
Chromosome 2	11011110 / 00011110
Offspring 1	1101111000110110
Offspring 2	1101100100011110

There are other methods for crossover. For instance more crossover points in one chromosome can be chosen. Crossover can be a very complicated procedure depending on the designer's choice.

3.6 Mutation

Random mutation changes a certain percentage of the bits in the list of chromosomes. It means mutation also tends to distract the algorithm from converging to a popular solution. In single point mutation, a 1 changes to a 0, and vice versa. Increasing the number of mutation increases the algorithm's freedom to search outside the current region of variable space. Mutation does not occur in the final iteration.

Original offspring 1	1101111000011110
Original offspring 2	1101100100110110
Mutated offspring 1	1100111000011110
Mutated offspring 2	1101101100110110

In Mutation process, there is a new generation of chromosomes with special combination of genes which are not in the previous generation. In fact Mutation process satisfies the request of chromosome variety in population of genetic algorithm. Indeed mutation provides chromosome.

3.7 Genetic algorithm parameters

There are two main parameters in genetic algorithm

- Crossover probability
- Mutation probability

Crossover probability shows the time period of crossover phenomenon and it is denoted by percentage. If crossover does not happen, the offspring just takes an exact copy from the parents' chromosomes; in case of crossover, the offspring takes some part of the parent's chromosomes. If all of the offspring produced by crossover, the crossover probability becomes 100% and if crossover probability is 0% it means the offspring just takes an exact copy of the parents' chromosome. Veritably crossover procedures are carried out to produce offspring having the advantageous part of the parents' chromosomes, thus new chromosomes have better quality.

Mutation probability shows the time period of chromosomes alter different parts. If there is not any Mutation in the process, the offspring is produced without any change after Crossover and if there is, just a part of the chromosome is changed. When mutation probability is 100%, chromosomes are altered and when probability of mutation is 0% chromosomes remains the same. The Mutation probability should have a moderate value, it should be chosen carefully. If it is high, genetic algorithm becomes a random search process.

There are other parameters for genetic algorithm, such as genetic population size. Genetic population size identifies the population of chromosome in one generation. Indeed if chromosome population is small, the probability of crossover process is lower and just a small part of search space is used. On the other hand if too many chromosomes are used, genetic algorithm speed will be reduced. Consequently, using big size population has a disadvantage for this algorithm which means computation time increases.

3.8 The process of Genetic algorithm

The entire process of genetic algorithm is summarized below:

1- [Start] genetic algorithm produces a random population includes N chromosomes. It means genetic algorithm producesa different solution for the problem.

2- [Fitness] genetic algorithm gives values for different solutions by means of fitness function.

3- [New population] genetic algorithm creates a new generation.

4- [Selection] genetic algorithm selects two parents from the existing chromosomes according to their fitness from initial population.

5- [Crossover] with specific percentage of crossover probability, new offspring are produced from parents.

6- [Mutation] with specific percentage of mutation probability, new offspring chromosome might be changed.

7- [Accepting] new offspring have been placed in a population.

8- [Replace] new produced population is used for running genetic algorithm.

9- [Test] if stopping condition is satisfied, genetic algorithm stops.

10- [Loop] go to the second step.

3.9 Stopping condition in genetic algorithm

Genetic algorithm same as other algorithm should have stopping condition. This condition can be chosen as one of following:

1- Producing at most "N" generation by means of genetic algorithm.

2- Time limitation which means after passing "T" time from the start of the process.

3- After producing several generations if there is not any better chromosome.

4- When one of the chromosomes is greater than or equal to a special fitness amount.

3.10 Different type of chromosome encoding

There are several different ways to encoding chromosome but with are looking for best way which is appropriate for the problem. Some of them are:

1- Binary form: in this method members are represented by bits, 1 and 0. Actually binary encoding is one of the popular methods in encoding. In this way chromosomes are encoded like this:

1010101011110011 binary encoding chromosome

2- Real valued form: if in solution a list of real valued results is wanted, encoding this list with real values is practical.

3- Regular form: this kind is used for organizing problems.

4- Tree form: in this form all of the population chromosomes can show as a tree with sine, add, sub or and functions and true false terminals. This method usually is used for inductive type programs and genetic programs because in this method Crossover and Mutation procedure is performed easily.

5- Continues type: this type of encoding is same as binary one, but the main advantage of it is using for continues variables [10].

In 1997 Kershenbaum found 5 specific points for encoding process which are:

1- It should be able to represent every solution.

2- It should be able to show just possible solutions.

3- All the possible solution should have the same chance.

4- It should give the best solution with fewer chromosomes.

5- Encoding method should have a tolerance space which means if the solution is to be changed; it can be changed from this special space in chromosome.

Although some of these conditions do not fit with each other they provide a way to find the most suitable encoding for the problem. After encoding chromosomes (solutions) they should be valued.

3.11 Selection method

According to the above mentioned explanations, chromosomes are selected from genetic population to be the parents for Crossover procedure. The main objective is how to select parents' chromosomes from the genetic population [11]. According to Darwin's theorem better chromosomes should continue their life and produce the next generation (survival of the fittest).

There are several ways to select the chromosomes.

1- Roulette wheel selection

2- Boltzman selection

3- Tournament selection

4- Rank selection

5- Steady state selection

Roulette wheel selection: in this method, selection is carried out regarding the fitness of the chromosomes; better chromosomes have more possibility to be selected. Actually in this method, chromosomes are placed to a place in a rotating wheel and after it stops specific chromosome is selected. Obviously chromosomes with more fitness amount have more chance to be selected.

Rank selection: if differences between fitness's in chromosomes are too much, the previous method is not useful. For instance, if one of the chromosomes has 90% fitness it means it is the best chromosome, so other chromosomes have less opportunity to be selected. In Rank selection method, first of all genetic population is classified, and then each chromosome takes a specific amount of fitness. In the worst case, chromosome has 1 of fitness and then 2… till "N", where "N" is population size. Therefore all the chromosomes have a chance to be selected. One of the disadvantages of this method is slow convergence.

Steady state selection: this method is not suitable for choosing parents; actually in this method most of the chromosomes should be alive, then by means of genetic algorithm just few of these chromosomes which have more fitness stay alive and make it to the next generation. After this procedure, new offspring replace the discarded chromosomes.

Tournament selection: in this method "K" chromosome is selected randomly from genetic population. Then the best chromosome is selected from those "K" chromosomes according to their fitness as shown in Figure 3.2.

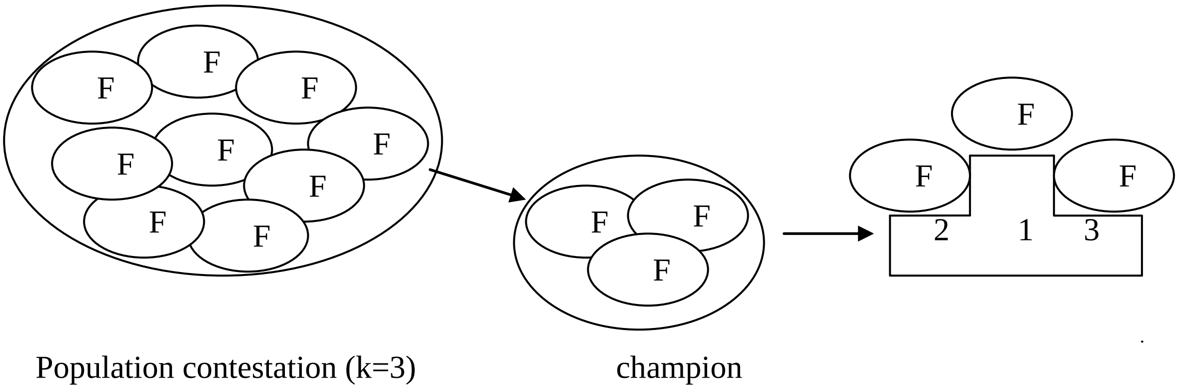

Figure 3.2: Tournament Selection Procedure [8].

where “K” is tournament size.

3.12 Crossover operation types:

In binary encoding there are two types of Crossover:

- Single point
- Multiple points.

In single point, a Crossover point is chosen and the first part of the chromosome is copied from one of the parents’ chromosome up to the crossover point and blended with the second part of chromosome of the other parent after crossover point (Figure 3.3) to create a new chromosome.

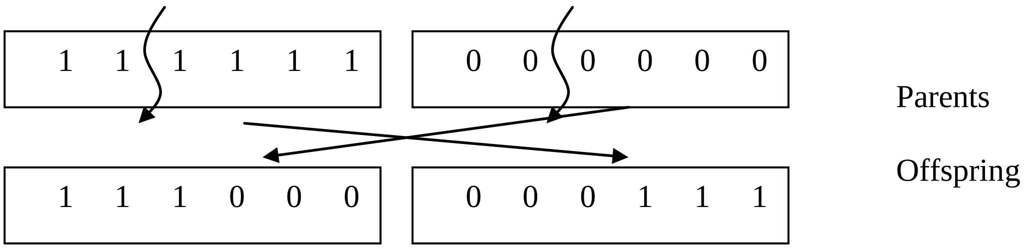

Figure 3.3: Single Point Crossover Procedure [8].

In two point method, two points are selected. Data of first parent's chromosome till first crossover point, data of the other parent's chromosome from first crossover point till second crossover point, and finally the remaining part from first parent are integrated to create a new chromosome.

Equal crossover: in this method bits are randomly copied from first and second parents.

Arithmetic crossover: in this case there are several arithmetical procedures performed to produce a child.

Regular encoding can be classified to single point and several points encoding. In Figure 3.4 the instance of regular type encoding can be seen.

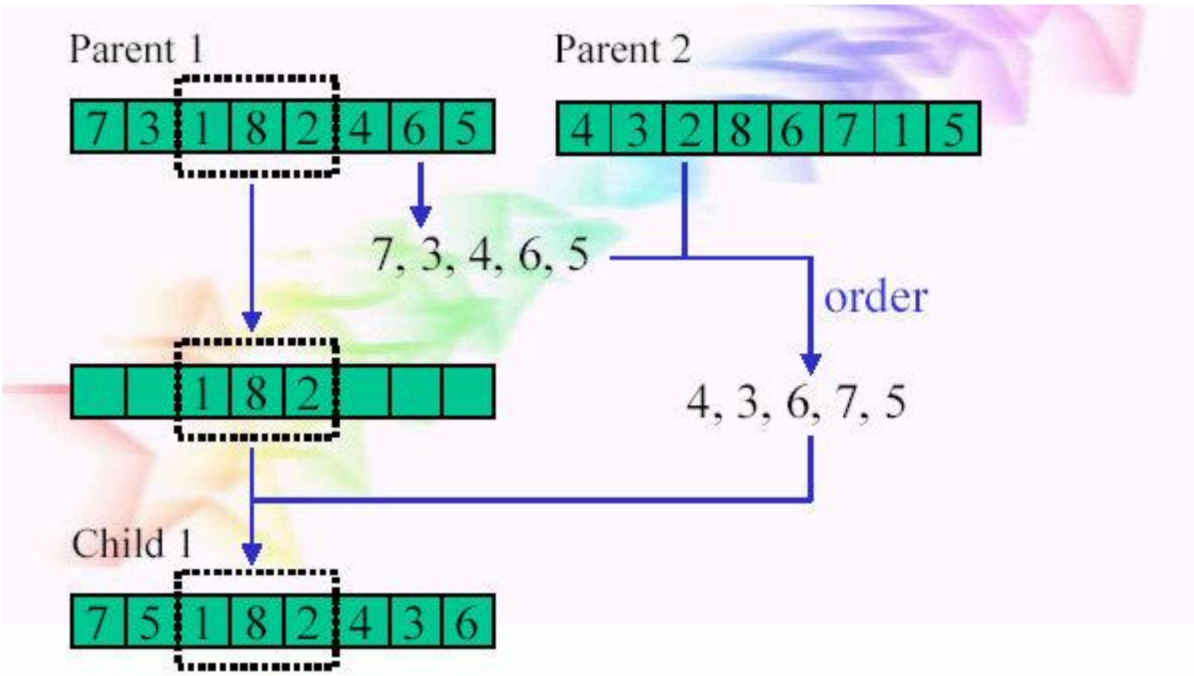

Figure 3.4: Regular Type Encoding [8].

3.13 Mutation types:

In binary mutation procedure, some of bits chosen randomly and changed their 1 to 0 or vice versa. Veritably in mutation process the main objective is producing well fit chromosomes (Figure3.5).

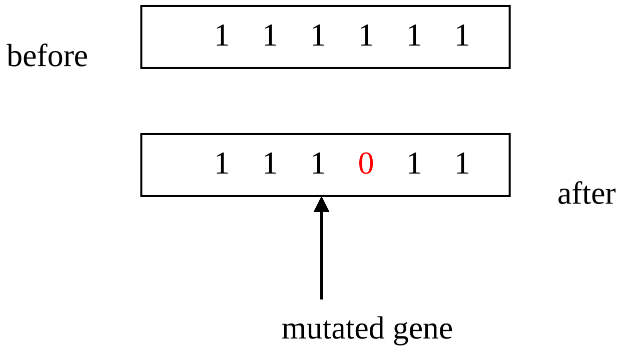

Figure 3.5: Mutation Procedure [8].

In regular mutation, the different chromosomes are selected randomly and changed as follows (Figure 3.6):

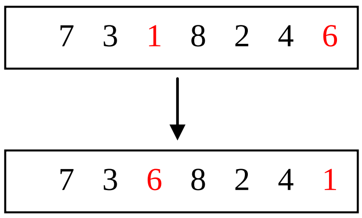

Figure 3.6: Regular Mutation [8].

In tree graph for mutation one node is replaced by the other one, which is shown in the Figure 3.7 below:

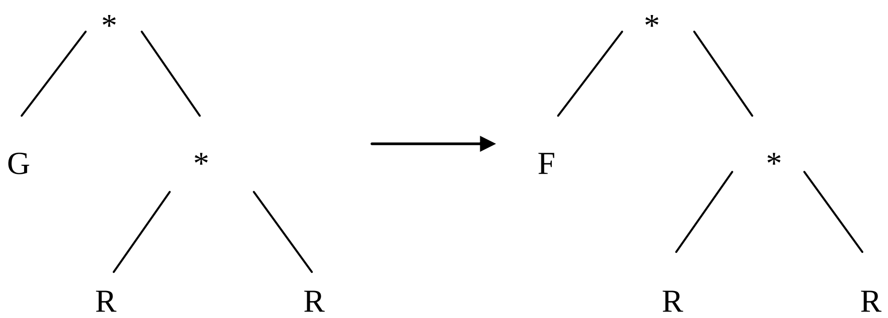

Figure 3.7: Tree Graph of Mutation [8].

Chapter 4

APPLICATION OF GENETIC ALGORITHM

In this study, contour of a hexagonal support insulator is optimized by genetic algorithm. In order to create the fitness function, finite element method is used to determine the electric field distribution.

By means of finite element method, electric field magnitudes are calculated and this information is fed to genetic algorithm in order to determine the optimum insulator geometry. The electrical field calculations have been carried out in COMSOL and GA solution has been created in MATLAB. Hexagonal insulator having a linear contour is drawn in COMSOL software by defined parameters of r_T and r_M. In this way, it is possible to link the finite element solution with genetic algorithm.

4.1 Finite Element Analysis

Figure4.1 shows the schematic of a support insulator having a hexagonal geometry. Insulator profile is taken to be linear. Because of the axial symmetry of hexagonal insulator, the problem is solved in two dimensional axi-symmetric space. For the axi-symmetrical insulator, the value of h, the height of the insulator, is kept constant at h = 40 mm. The radius (r_s) and the height (h_s) of screw socket using for connections are also kept constant during the calculations. The dimensions of the screw sockets are r_s = 3 mm, and h_s = 10 mm. In this study, by varying r – coordinates of the top point (r_T), and the medium point (r_M) of the insulator, different contours are obtained. The main challenge in this study is defining top and the medium radii of the insulator as parameters and creating a function for the solution to link FEM solution with genetic algorithm [21].

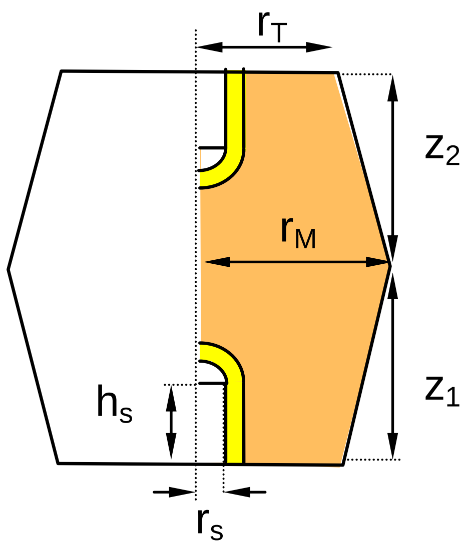

Figure 4.1: Support Insulator to be Optimized

A three dimensional figure of the insulator is given in Figure 4.2.

Figure 4.2:3-D Representation of the Hexagonal Insulator

The epoxy resin insulator is placed between plane – plane electrode system. The permittivity of epoxy resin is 5. In this study, it is considered that the magnitude of the potential difference as 1 kV which represents percent potential difference for studying the efficiency of the method. Top electrode is the live electrode with a boundary condition of 1 kV and the bottom electrode is the ground with zero potential. The entire physical problem includes domain of air with permittivity of 1.All the domains in the problem are defined by their permittivities. Interface between the insulator and air is set to be zero charge/symmetry.

After appointing all the boundary conditions and defining the domains in COMSOL software, the mesh is created for discretization procedure. During discretization process, a linear algebraic system is created by writing down the basic equations for each element. The equation system is then solved by an iterative algorithm. After solving equations for each element; the solution is recombined to have general solution for potential and electric field. By running COMSOL software the insulator area is divided into 1767 elements. It takes 5 seconds to create the entire mesh, which means in a very short time, insulator area can be discretized. A sample for the mesh is shown in Figure 4.3.

Solving equations in finite element method can be carried out by using different elements other than triangles. However, using triangles gives a relatively simpler equation system than rectangles to solve since each element has three corners. Additionally, using triangles makes it easier to represent especially the complicated boundaries or domains. The element size is adjustable in COMSOL. By reducing the element size it is possible to use many of them in the problem, therefore, the model becomes very similar to real physical problem [22-23]. That helps increasing the accuracy of the solution. In each element in order to find the magnitude of potential and electric field, one can refer to the Chapter 2.

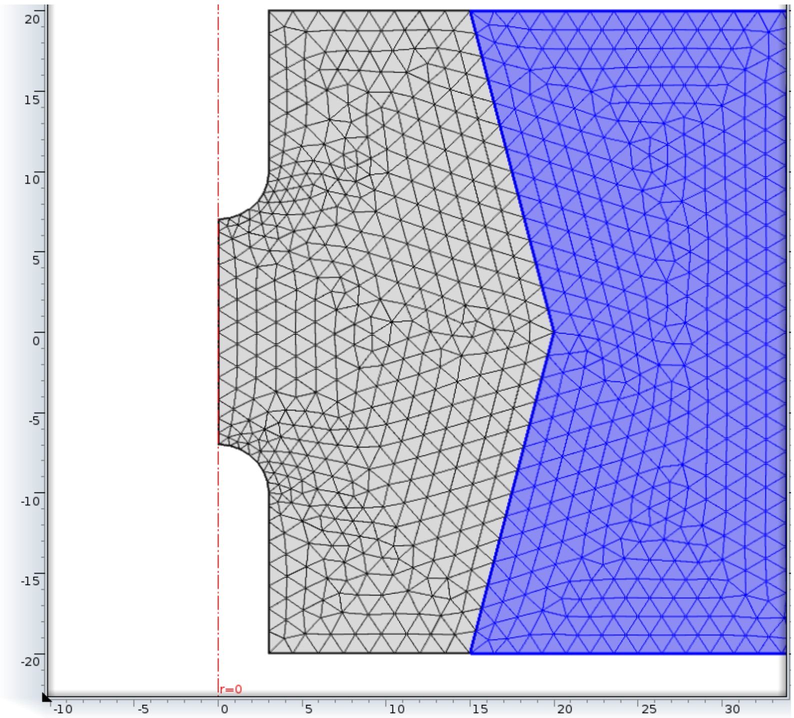

Figure 4.3: A Sample FEM Mesh for Hexagonal Insulator

One of the COMSOL software advantages is ability to show all procedures schematically after performing it. For instance, after calculations, COMSOL draws the potential distribution as seen in Figure4.4.

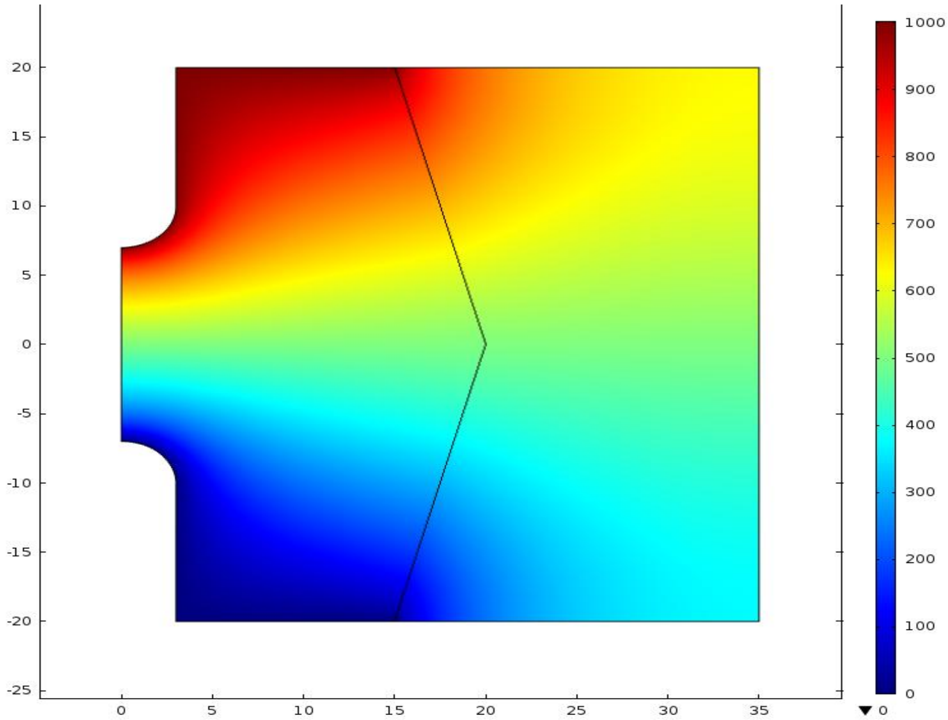

Figure 4.4: Insulator Surface Potential Distribution

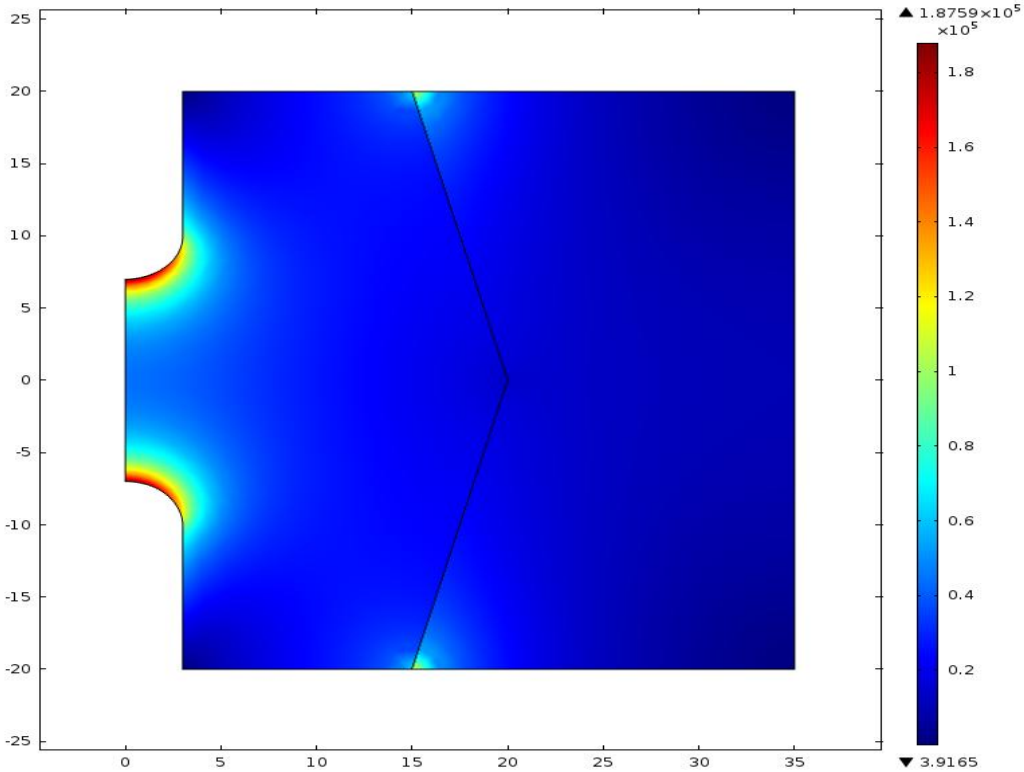

Figure 4.5: Electric Field Distribution

The design variables are r_T and r_M since the insulator has a linear contour. Z_1 and Z_2 are fixed at – 20 and 20 mm respectively. The r coordinates of the linear contour can be defined as follows:

$$r = \begin{cases} r_M + \left[\frac{z(r_M - r_T)}{z_1}\right] & z_1 \le z \le 0 \\ r_T + \left[\frac{(z - z_2)(r_M - r_T)}{z_2}\right] & 0 \le z \le z_2 \end{cases} \tag{4.1}$$

Because of the symmetry argument, tangential electric field in question is calculated in r and z coordinates separately. In order to find the electric field which forces to a flashover along the surface, total tangential electric field should be determined:

$$E_t = \sqrt{(E_{tr})^2 + (E_{tz})^2} \tag{4.2}$$

where E_t is the total tangential electric field; E_{tr} is r component of the tangential electric field E_{tz} is the z component of the tangential electric field. In Figure 4.6 tangential electric field with respect to r-coordinate along the insulator surface is shown. As seen in the figure below, as the distance between the point on the insulator surface and live conductor get higher, tangential electric field decreases.

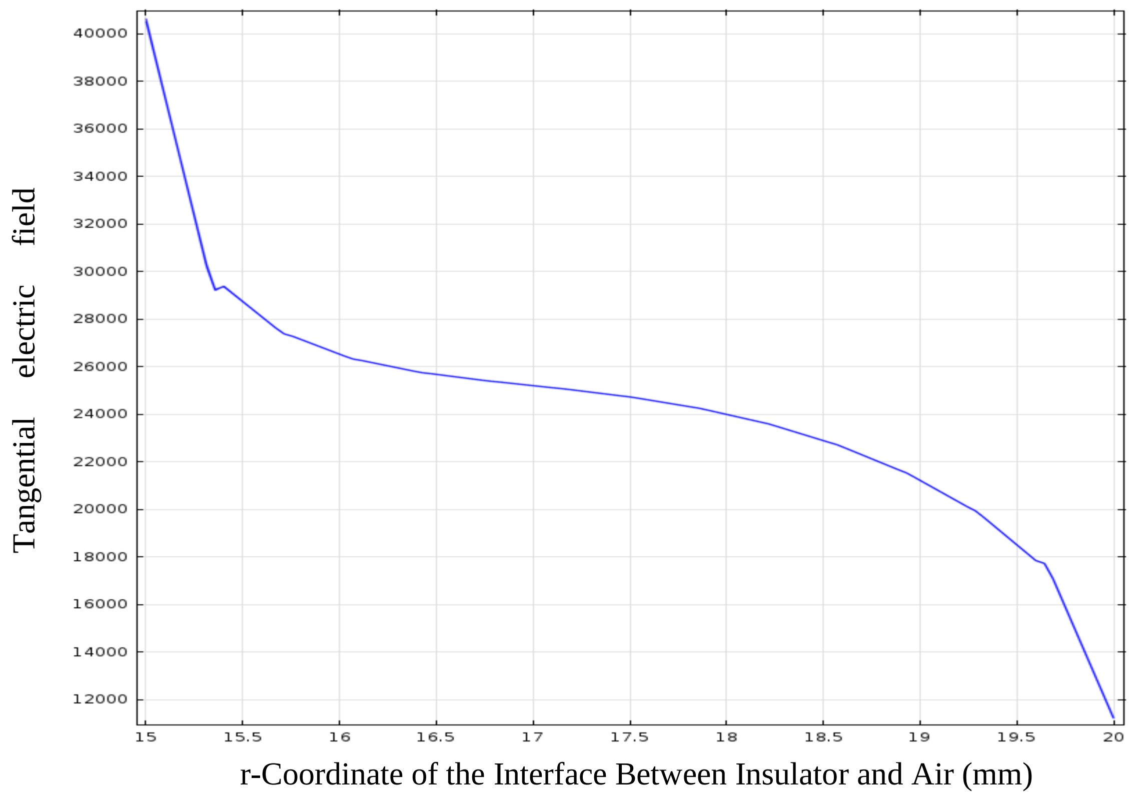

Figure 4.6: Tangential Electric Field According to r-Coordinate of Insulator

The main objective in this study is to obtain as uniform and minimum tangential electric field as possible. Since the field distribution depends on the geometry, the problem becomes obtaining uniform field distribution with optimum geometry

4.2 Genetic algorithm

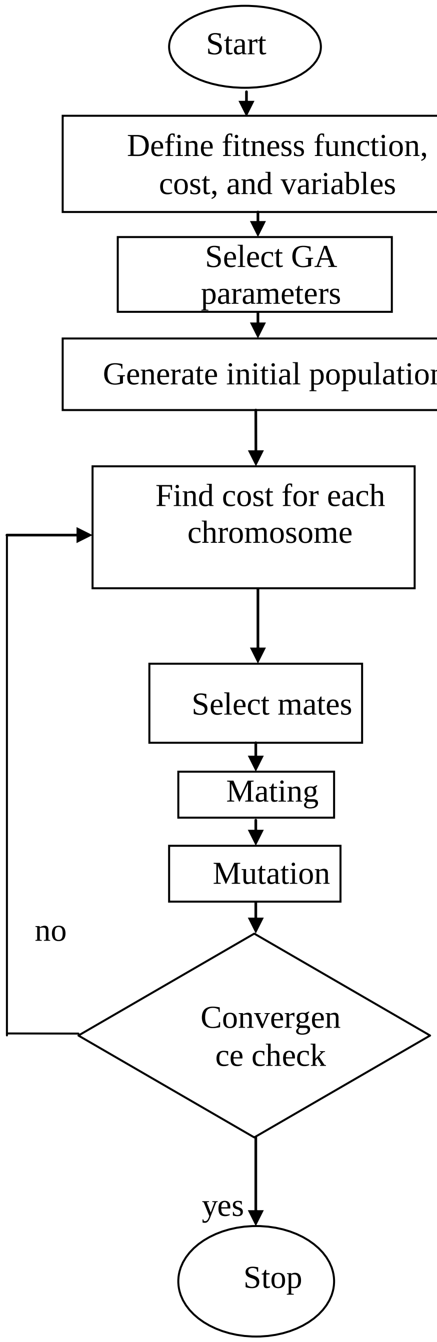

Figure 4.7: Genetic Algorithm Flowchart

In primary step, design variables, fitness function and genetic algorithm parameters which are; population size, selection rate, mutation rate should been identified.

The problem has two design variables which are the top and medium radii for the hexagonal insulator. Search spaces for them are designated to be in the range between 14 – 16 for r_T and 18 – 22 for r_M.The initial population is created randomly by using those two variables. r_T and r_M is selected from their search space and in COMSOL software, Laplace's equation is solved and the tangential electric field is calculated. For the process of electric field calculations, one can refer to Chapter2. After initial population, genetic algorithm procedure is applied to determine the optimum solution as discussed in Chapter 3.

This optimization problem has two objectives, having the tangential electric field as uniform as possible while keeping it as minimum as possible. In order to obtain this, mean and standard deviation of the tangential electric field along the insulator surface are determined with respect to finite element solution. The cost function can be defined as follows:

$$f = w_1 \mu_E + w_2 \sigma_E \tag{4.3}$$

Where μ_E is the mean of the tangential electric fields and σ_E is the standard deviation of the tangential electric fields along the insulator surface.Having more than one objective requires normalization because the average electric field and standard deviation are different in magnitudes and units. For that reason, the weights are used to make these objectives comparable before summation [25]. The weights are set as $w_1 = 10^{-4}$ and $w_2 = 10^{-3}$.

To be able to use this cost function with the identified variables, COMSOL is linked to MATLAB by a function created for the entire finite element solution in

MATLAB. Then the result of the average tangential electric field and standard deviation of the tangential electric field along the insulator surface can be calculated in MATLAB and fed to genetic algorithm.

4.3 Optimization

Behavior of genetic algorithm against the population size is very noticeable. The large size of population do not help genetic algorithm to find the best solution all the time, which means it does not help to improve the speed of genetic algorithm process. The optimum genetic population is 20 or 30, but actually the best size depends on the encoding type. It means when for 32 bits chromosomes the population size should be different than when it is 16 bits.

The main purpose in this procedure is finding the minimum cost function with optimum parameters, therefore experiments are done by different criterion which are different amount of population size and mutation rate and number of generation focus to effect of them in the result (cost function). The selecting method for genetic algorithm is randomly, and after compared the results try to focus on modify the parameters which make the cost function more minimum than the others. These results collect in table below.

The number of bits is changed from to represent r_T and r_M between 6 and 10 bits. In order to create a bigger searching space, population size is changed from 16 to 40 in this study. The mutation rate is changed between 0.02 and 0.25. For algorithm is run for different iteration. Optimum coordinates for the hexagonal insulator are given in the Table 4.1.

Table 4 1: Results for Different Parameters

# of Bits	Pop. Size	# of Iterations	Mutation rate	rt (mm)	rm (mm)	Cost
8	16	20	0.15	18.3608	14.1804	2.8268
8	16	20	0.02	18.1255	14.0627	2.8718
8	16	20	0.05	19.6941	14.8471	2.8543
7	20	30	0.2	21.2756	15.6378	2.5465
8	30	30	0.25	18.3294	14.1647	2.4216
7	20	20	0.1	18.5079	14.254	2.5502
6	10	20	0.12	20.7937	15.3968	2.9973
6	40	20	0.2	20.2222	15.1111	2.3473
10	30	30	0.25	20.2362	15.1181	2.5534
7	20	20	0.02	21.2784	15.6392	2.6001
6	40	20	0.25	19.0794	14.5397	2.3495
10	40	20	0.2	18.8055	14.4027	2.3515

As it is shown in the Table 4.1, different experiments are performed with different parameters. The worse result in above table is for the population size of 10. Therefore, it is better to avoid population size smaller than 10 for further studies. Table 4.1 is separated to sub-tables in order to show the process in detail.

Table 4 2: The Effect of Change in Mutation Rate

# of Bits	Pop. Size	# of Iterations	Mutation rate	rt (mm)	rm (mm)	Cost
8	16	20	0.15	18.3608	14.1804	2.8268
8	16	20	0.02	18.1255	14.0627	2.8718
8	16	20	0.05	19.6941	14.8471	2.8543

In the Table 4.2, all the parameters are fixed except the mutation rate in order to investigate the effect of mutation rate. Increasing the mutation rate, cost function decreases. During the experiments, it is seen that after 20 iterations, there is no significant change in cost amount. Therefore, iterations are done between 20 and 30.

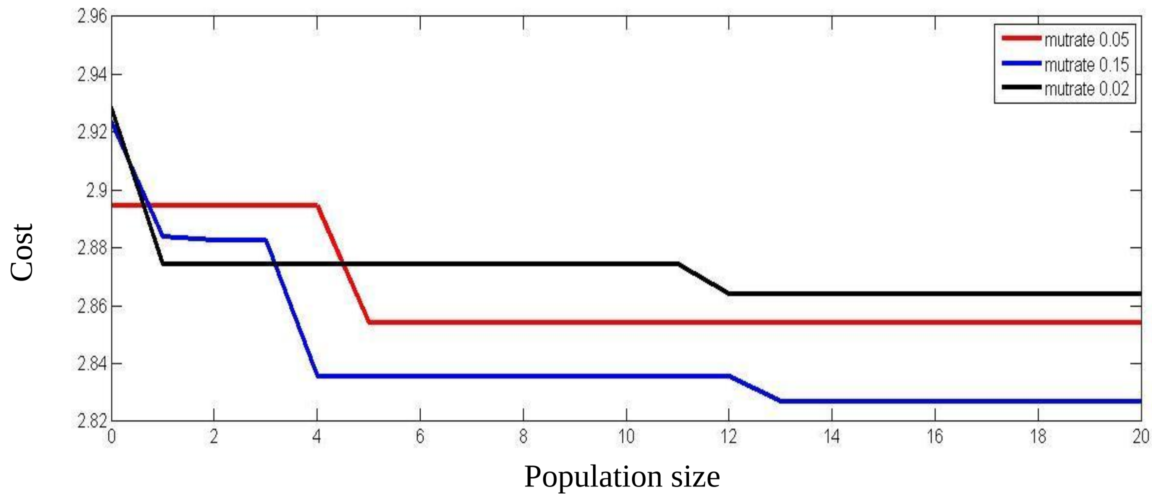

Figure 4. 8: Comparing cost function of different mutation rate for population size = 16

Asshown in the Figure 4.8, cost functions are compared for three different mutation rates, 0.2, 0.15 and 0.05 for population size of 16 and it is seen that, by increasing the mutation rate the cost function gets better.

Table 4 3: The Change in the Cost Function for 20 Individuals in the Population

# of Bits	**Pop. Size**	**# of Iterations**	**Mutation rate**	**rt (mm)**	**rm (mm)**	**Cost**
7	20	20	0.2	21.2756	15.6378	2.5465
7	20	20	0.1	18.5079	14.254	2.5502
7	20	20	0.02	21.2784	15.6392	2.6001

In the Table 4.3, the mutation rate is changed from 0.02 to 0.1 and 0.2 for 20 individuals in the population. It is seen that, by increasing the mutation rate, cost function gets smaller.

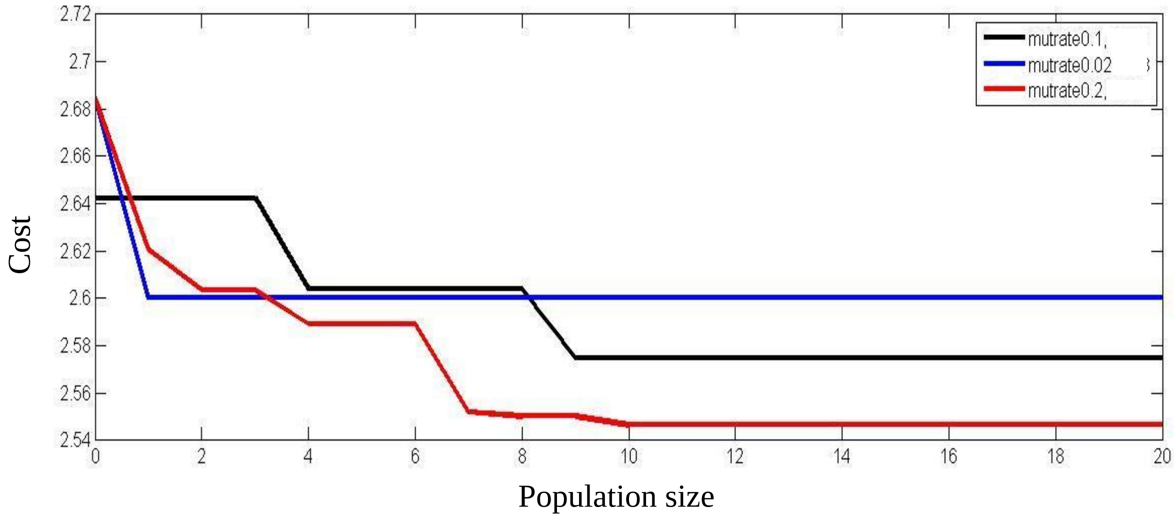

Figure 4.9: Comparing Cost Function of Different Mutation Rate
for Population Size =20

In the Figure 4.9, the best cost curve is for mutation rate = 0.2 and number of bits 7 and it is denoted by red.

It is observed that, an increase in the population size gives better the results; experiments are continued for population size = 30 and 40 in the following tables.

Table 4 4: Comparing Number of Bits for 30 Individuals

# of Bits	**Pop. Size**	**# of Iterations**	**Mutation rate**	**rt (mm)**	**rm (mm)**	**Cost**
10	30	30	0.25	20.2362	15.1181	2.5534
8	30	30	0.25	18.3294	14.1647	2.4216

For 30 individuals in the population with 0.25 mutation rate, change in the number of bits gives the results shown in Table 4.4 and Figure 4.10.

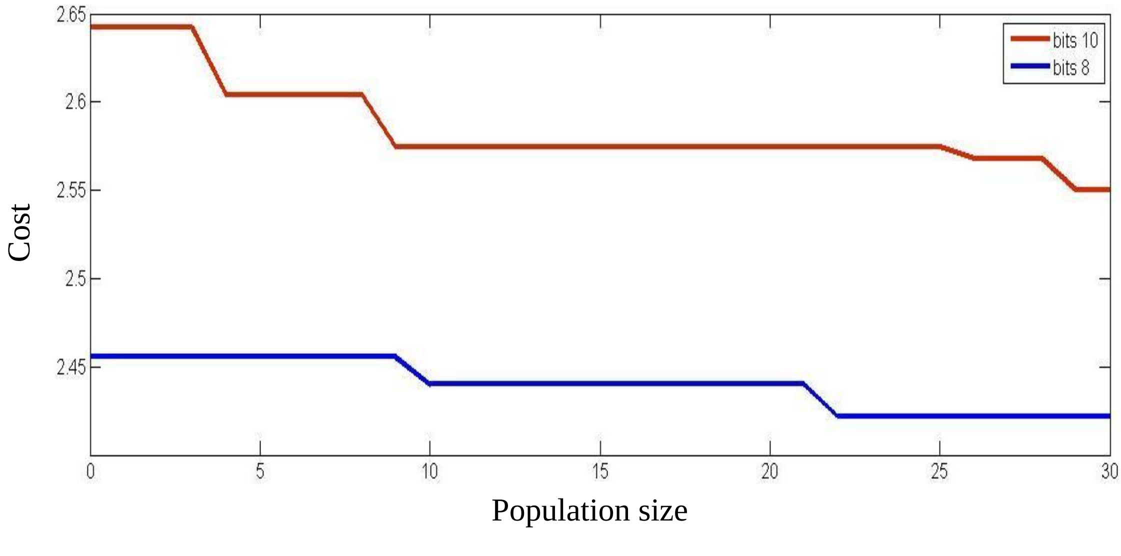

Figure 4.10: Comparing Cost Function of Different Number of Bits for Population Size =30

In the Table 4.5, change in mutation rate is investigated for 40 individuals in the population.

Table 4 5: Change in Mutation Rate for 40 Individuals

# of Bits	**Pop. Size**	**# of Iterations**	**Mutation rate**	**rt (mm)**	**rm (mm)**	**Cost**
6	40	20	0.2	20.2222	15.1111	2.3473
6	40	20	0.25	19.0794	14.5397	2.3495
6	40	20	0.15	20.3344	15.2211	2.3516

Table 4 6: Comparing Number of Bits for 40 Individuals

# of Bits	**Pop. Size**	**# of Iterations**	**Mutation rate**	**rt (mm)**	**rm (mm)**	**Cost**
6	40	20	0.2	20.2222	15.1111	2.3473
10	40	20	0.2	18.8055	14.4027	2.3515
8	40	20	0.2	20.1961	15.098	2.3476

Tables 4.5 and 4.6 show the change in cost function for population size of 40 with different mutation rate and number of bits. In this case, first the number of bits is fixed and the mutation rate is changed; then for the mutation rate of 0.2 the number of bits is changed not smaller than 6.

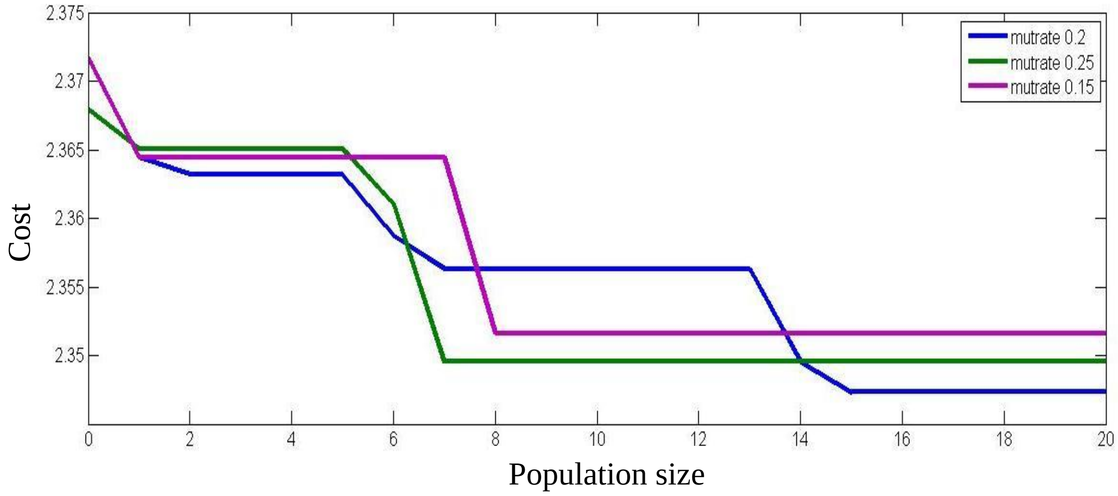

Figure 4.11: Comparing Cost function of Different Mutation Rate for Population Size = 40

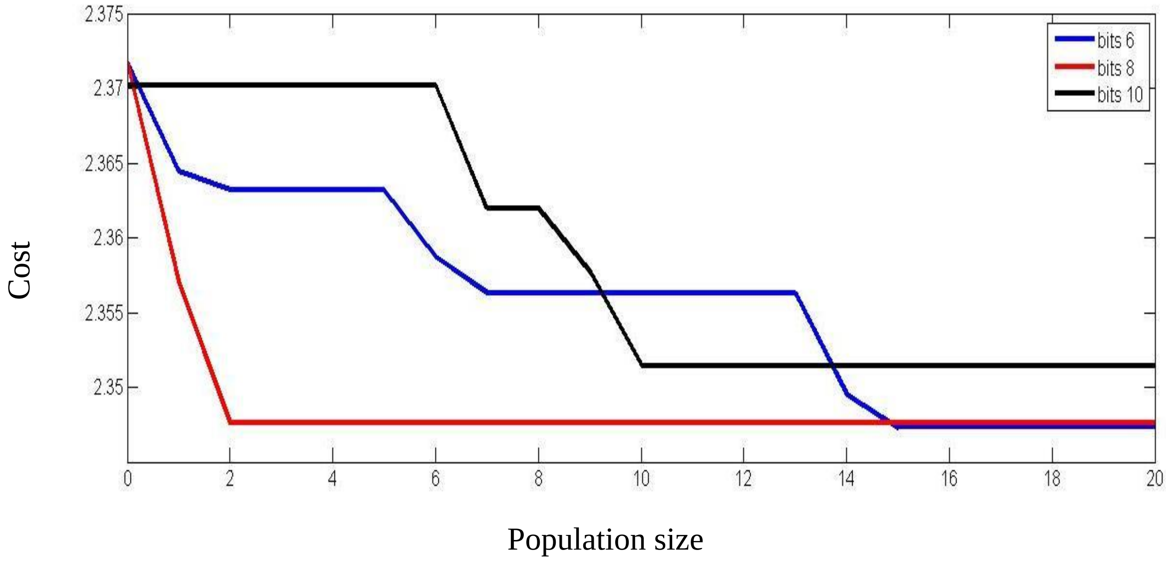

Figure 4.12: Comparing Cost Function of Different Number of Bits for Population Size =40

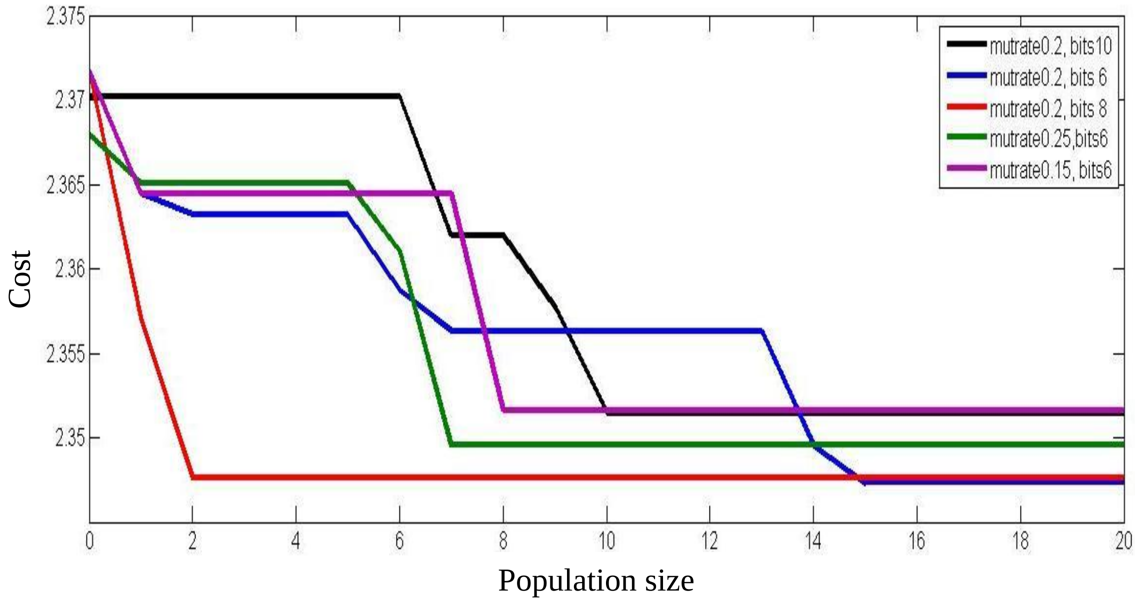

Figure 4. 13: Comparing Cost Function for Population Size =40

As it is shown in the Figure 4.13, the blue curve with population size = 40, mutation rate = 0.2, number of bits = 6 and cost = 2.3473 is found to be the best result for this study. Therefore r_T = 20.2222 and r_M = 15.1111 are accepted as an optimum amount for hexagonal support insulator which is achieved in MATLAB. Compared to the other studies in the literature, it is a reasonable amount of time to get the optimum result. The results are also compatible with the literature [13-19].

Chapter 5

CONCLUSION AND FUTURE WORK

5.1 Conclusions

This study has proposed a method for optimizing insulator geometry. There are many optimization methods for those kinds of problems. The genetic algorithm (GA) is shows good performance in global search problems for design optimization as well as this study.

Optimum insulator geometry is obtained by having the tangential field distribution along the insulator surface as minimum and uniform as possible. In order to achieve the desired field distribution, an objective function is defined to be minimized which includes standard deviation to supply uniformity, and mean value for minimization [25- 26]. As a result, the optimum geometry has a tangential electric field distribution along the insulator surface uniform and minimum compared to the other solutions.

During the genetic algorithm applications, since the algorithm is sensitive to initial population and genetic parameters, the best result cannot be achieved all the time. Therefore, different parameters should be analyzed. Different mutation rates, number of bits, population sizes are investigated for different number of iterations in order to find the optimum solution.

The results of genetic algorithm are compatible with Neural Network solutions in the literature. Finite Element Method is also reduces the computation time compared to

Charge Simulation Method. Using Finite Element Method for field distribution calculations makes the solution more understandable, more flexible and equally accurate.

Solving this optimization problem by means of genetic algorithms gives effective results. Contour optimization studies as in this thesis, decreases the cost of experimental methods.

5.2 Future work

For the future studies, optimizing different types of insulators with complicated geometries is planned. The efficiency and speed of the GA code is intended to be improved by using adaptive mutation rate and adjustable crossover rate.

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