ACTIVE ARRAY ANTENNA ELEMENT FAILURE PATTERN ANALYSIS AND SYNTHESIS USING GENETIC ALGORITHM

ABSTRACT

Active antenna arrays are used to increase the gain and provide electronic steering, which is more effective when compared to a single antenna. However, element failure in the active antenna array may hamper the performance of the active antenna array.

A heuristic method using Genetic Algorithm is proposed for element failure mitigation in active antenna arrays. The Antenna arrays considered are of linear, rectangular, hexagonal and rhombic shapes and the element failures occurring are as distributed and concentrated. The Element failure Pattern of the handicapped antenna array is analyzed. In this approach, Genetic Algorithm is applied on the amplitude weights of the active elements and the new pattern is synthesized, which is a close approximation to the original pattern of the perfect antenna array.

CONTENTS

CHAPTER 1

ANTENNA BASICS

CHAPTER 1: ANTENNA BASICS

1.1 ANTENNAS – AN INTRODUCTION:

An *antenna* is defined as the structure associated with the region of transition between a guided wave and a free-space wave, or vice-versa [4], [22].

1.1.1 Basic Equation of Radiation:

— —

Where, L = length of current element, m

— = time-changing current, A s^{-1}

Q = charge, C

— = time-change of velocity which equals the acceleration of charge, m s^{-2}

In Fig. 1.1, there is a communication link established between transmitting antenna and the receiving antenna via free-space. The receiving antenna is remote from the transmitting antenna so that the spherical wave radiated by the transmitting antenna arrives as an essentially plane wave at the receiving antenna.

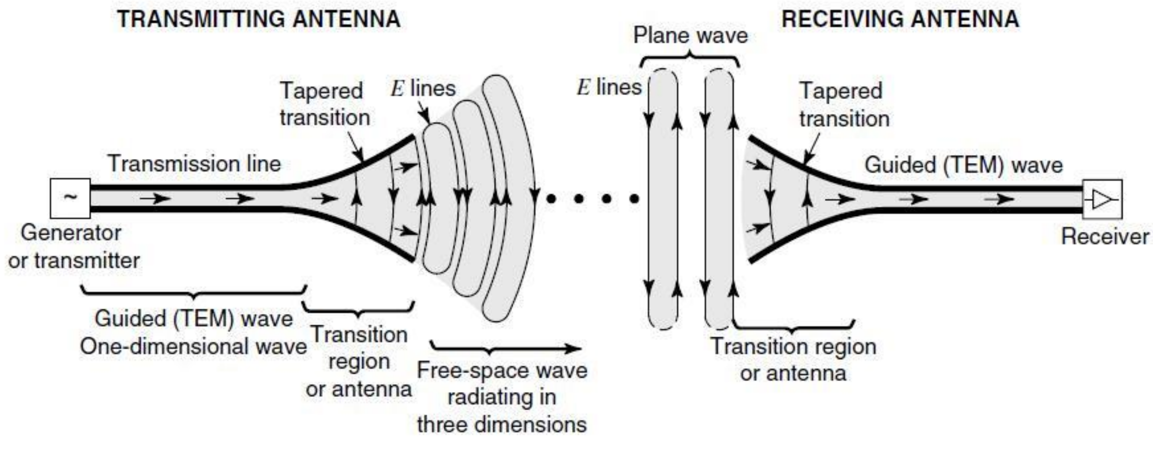

Figure 1.1: Radio Communication Link

1.1.2 Patterns:

The term *Radiation Pattern* refers to the directional (angular) dependence of the strength of the radio waves from the antenna or other source.

The fields around an antenna may be divided into two principal regions, one near the antenna called the *near field* or *Fresnel zone* and one at a large distance called the *far field* or *Fraunhofer zone* [21]. The boundary between the two may be arbitrarily taken to be at a radius

Where, L = maximum dimension of the antenna, m

λ = wavelength, m

Power Pattern:

Power Pattern is the plot of power density (*Poynting vector*) as a function of space coordinates. According to Poynting's theorem,

Polarization Pattern:

Polarization Pattern is the plot of polarization property of the field vector $\vec{}$ as the function of (coordinates.

Field Pattern:

Field Pattern is the plot of electric field intensity as a function of space coordinates. This is also equivalent magnetic field intensity,

Near-field pattern or *Fresnel pattern* refers to the positional dependence of the electromagnetic field in the near-field, or Fresnel region of the source. The near-field pattern is most commonly defined over a plane placed in front of the source, or over a cylindrical or spherical surface enclosing it, used in fiber-optics, lasers, integrated optics etc.

The far field radiation pattern may be represented graphically as a plot of one of a number of related variables, including; the field strength at a constant (large) radius (an amplitude pattern or field pattern), the power per unit solid angle (power pattern) and the directive gain. Very often, only the relative amplitude is plotted, normalized either to the amplitude on the antenna bore sight, or to the total radiated power. The plotted quantity may be shown on a linear scale, or in dB. The plot is typically represented as a three dimensional graph, or as separate graphs in the vertical plane and horizontal plane. This is often known as a *polar diagram*.

1.1.2.1 Reciprocity:

It is a fundamental property of antennas that the receiving pattern (sensitivity as a function of direction) of an antenna when used for receiving is identical to the far-field radiation pattern of the antenna when used for transmitting. This is a consequence of the reciprocity theorem of electromagnetics. Therefore in discussions of radiation patterns the antenna can be viewed as either transmitting or receiving.

1.1.2.2 Sensitivity:

The sensitivity of a receiver is the smallest amount of power that can be input to the receiver, such that the receiver can still maintain reliable communication. *Total Isotropic Sensitivity*, or TIS, is a measure of the average sensitivity of a receiver-antenna system, when averaged over the entire 3-dimensional sphere. The result will be strongly related to the antenna's radiation pattern.

1.1.2.3 Gain:

The term Antenna Gain describes how much power is transmitted in the direction of peak radiation to that of an isotropic source. An antenna with a gain of 3 dB means that the power received far from the antenna will be 3 dB higher (twice as much) than what would be received from a lossless isotropic antenna with the same input power.

1.1.2.4 Typical Patterns and Terminology:

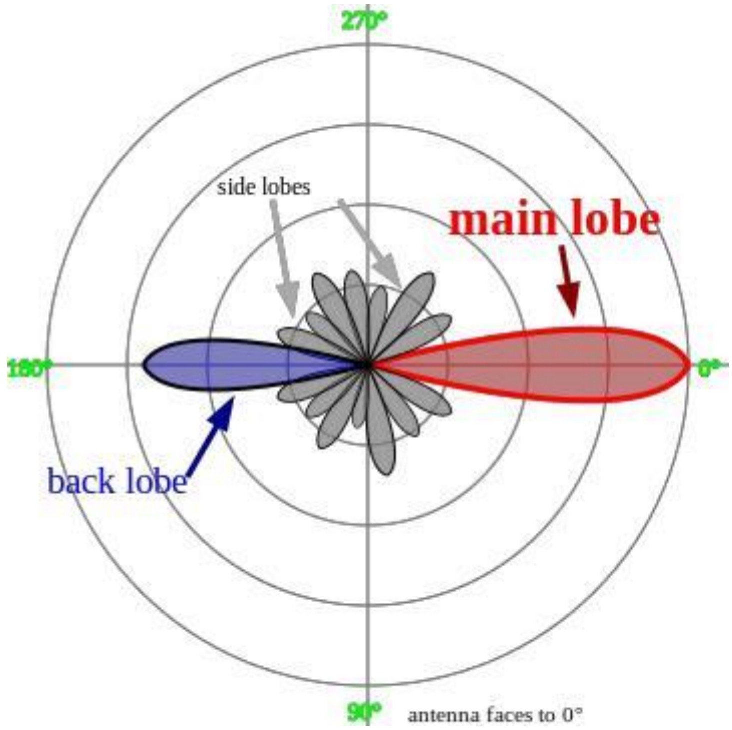

Figure 1.2: A typical 3D Radiation plot

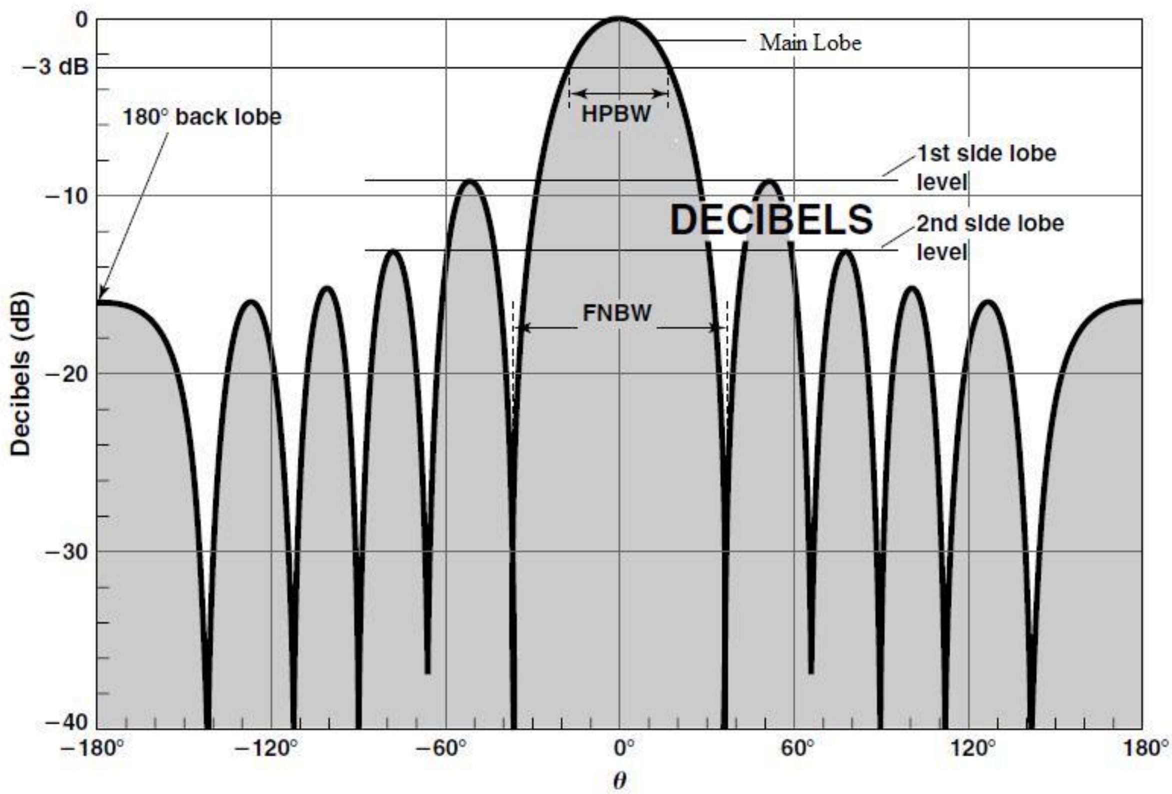

Figure 1.3: 2D Radiation plot

Radiation Lobes:

The radiation pattern shows a pattern of *lobes* at various angles, directions where the radiated signal strength reaches a maximum, separated by *nulls*, angles at which the radiated signal strength falls to zero [5].

In a directional antenna in which the objective is to emit the radio waves in one direction, the lobe in that direction has a larger field strength than the others; this is the *main lobe*. The other lobes are called *side-lobes*, and usually represent unwanted radiation in undesired directions. The side-lobe in the opposite direction (180°) from the main lobe is called the *back lobe*. In transmitting antennas, excessive side-lobe radiation wastes energy and may cause interference to other equipment. In receiving antennas, side-lobes may pick up interfering signals, and increase the noise level in the receiver.

The power density in the side lobes is generally much less than that in the main beam. It is generally desirable to minimize the side-lobe level (SLL), which is measured in decibels relative to the peak of the main beam. The main lobe and side-lobes occur for both conditions of transmit, and for receive.

X	Radiation Pattern	Explanation
0	0 dB	Peak of main beam
3.14 =	- dB	First null
4.49 —	-13.26 dB	Peak of first side-lobe
6.28 =	- dB	Second null
7.72 —	-17.83 dB	Peak of second side-lobe

Table 1.1: Pattern values for a rectangular aperture antenna

Half Power Beamwidth (HPBW):

HPBW is defined as an angular width in degree measured on the main lobe between the points where the radiation power has fallen to half of its maximum value or field intensity is 0.707 times of its maximum value [4].

First-Null Beamwidth (FNBW):

FNBW is defined as the angular width in degree between first nulls on the either side of main lobe.

Mean of Side-lobes:

Mean is obtained by dividing the sum of all side-lobe levels present in the pattern by the total number of side-lobes present.

$$- \quad \Sigma$$

Standard Deviation of Side-lobes:

Standard deviation (σ) shows how much variation or dispersion exists from the average side-lobe levels.

$$\Sigma \quad -$$

1.2 ANTENNA ARRAYS:

An antenna array is a group of radiators whose currents are of different amplitudes and phases. They use electromagnetic wave interference phenomena to enhance the radiative signal in the desired direction and diminish it in the non-desired direction [23].

In general, the excitation of an array consists of amplitude and a phase at each element. This discrete distribution is often called an aperture distribution, where the discrete array is the aperture. The far-field radiation pattern is just the discreet Fourier transform of the array excitation.

Antenna arrays are becoming increasingly important in wireless communications. The main advantages of using antenna arrays:

1. They can provide the capability of a steerable beam (radiation direction change) as in smart antennas.
2. They can provide a high gain (array gain) by using simple antenna elements.
3. They provide a diversity gain in multipath signal reception.
4. They enable array signal processing.

<u>Types of Antenna Arrays:</u>

i. Linear Antenna Array: The antenna array is said linear if the elements of antenna array are equally spaced along a straight line. The linear antenna array is said to be uniform linear array if all the elements are fed with a current of equal magnitude with progressive uniform phase shift along the line

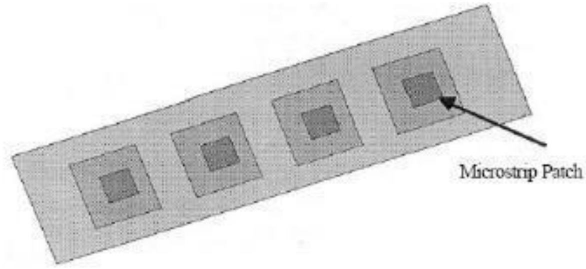

Figure 1.4: Linear Array Antenna

ii. Planar arrays: An antenna array in which all the elements lie along the same plane. Such an array may incorporate parasitic elements, and if the array is phased, multiple identical beams may be transmitted simultaneously. Planar arrays can be implemented as rectangular, hexagonal and circular etc.

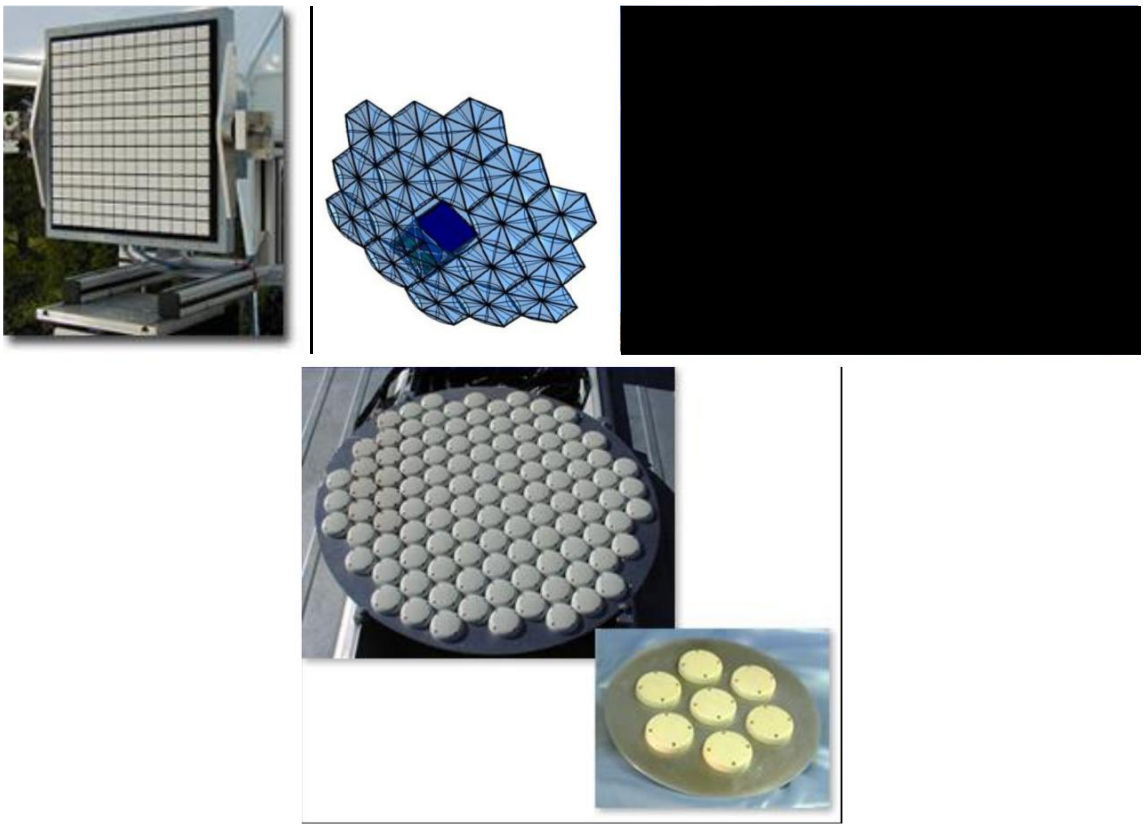

Figure 1.5: (*Clockwise from top-left)* Rectangular Antenna Array, Hexagonal Antenna Array, Rhombic Antenna Array, and Circular Antenna Array

iii. Three-Dimensional Antenna Arrays: A Three-dimensional antenna array is an antenna array in which all the elements lie in all the three coordinates.

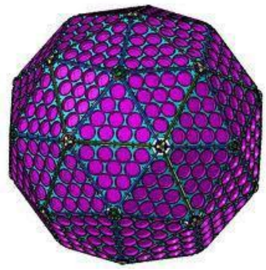

Figure 1.6: Three-Dimensional Antenna

1.2.1 Pattern:

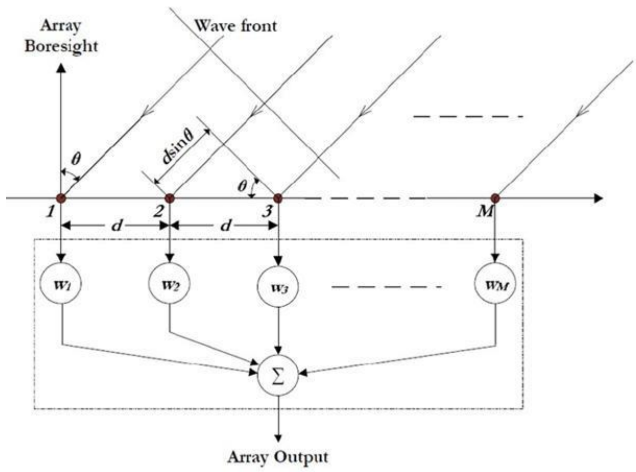

Figure 1.7: Linear Antenna Array

The figure shows a linear array of M elements; the parallel wavefronts of a far field (received signal) incident on the array are shown. The distance between the antenna elements are uniform with a separation ‗d‘. w_1, w_2,…. w_n are the weightings or excitation of the individual antenna element [11]. Thus the output is given by:

Where,

Σ

Where, = amplitude weights,

= propagation constant = —

= polar angle for beam peak

The one-dimensional array factor is only a function of the polar angle. Hence, the array can filter signals based on their polar angle θ but cannot distinguish arriving signals based on the azimuth angle φ.

Uniform array nulls and side-lobes are well behaved and equally spaced. A convenient term is side-lobe ratio, which is the ratio of the main beam amplitude to that of the first side-lobe. For large arrays, the side-lobe ratio (SLR) is the same as that for uniform line sources, and is independent of the main beam angle. It is 13.26dB.

The spatial aliasing effect causes some side-lobes to become substantially larger in amplitude, and approaching the level of the main lobe; these are called *grating lobes*, and they are identical, or nearly identical in the example shown, copies of the main beams [24]. Grating lobes are a special case of a side-lobe. In such a case, the side-lobes should be considered all the lobes lying between the main lobe and the first grating lobe, or between grating lobes. It is conceptually useful to distinguish between side-lobes and grating lobes because grating lobes have larger amplitudes than most, if not all, of the other side lobes. The mathematics of grating lobes is the same as of X-ray diffraction.

The equation for maximum spacing is a function of wavelength of operation and maximum look angle [26]:

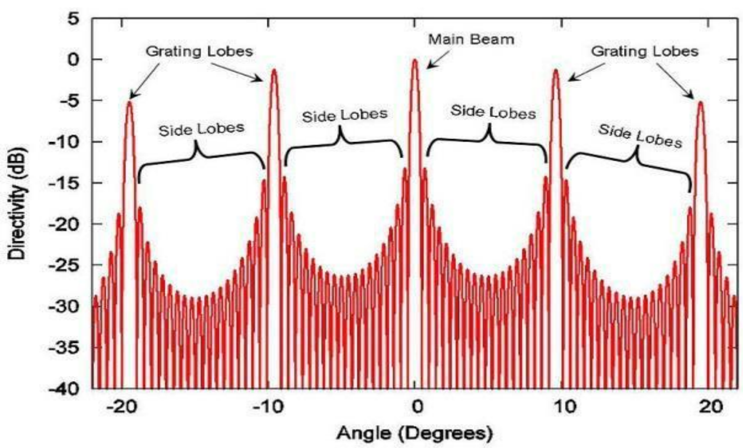

Figure 1.8: Grating Lobes

Thus, for one-dimensional array pattern equation can be summarized mathematically as:

$\sum$ elements

Thus, for two-dimensional array of (N x M) elements, the pattern equation can be given as:

$\sum\sum$

Where, — is the propagation constant, =amplitude weights, d=antenna spacing

CHAPTER 2

ELEMENT FAILURE

AND

ITS PATTERN ANALYSIS

CHAPTER 2: ELEMENT FAILURE AND ITS PATTERN ANALYSIS

2.1: ELEMENT FAILURE:

An element in an antenna array is said to be failed, if it fails to receive the incident signal. Element failure in antenna arrays deforms the pattern and degradation is mostly in the form of increased side-lobe level (SLL).

An increase in the SLL may result in interference from the other signal and creates a noise in the receiver, resulting in ambiguity in the location of the target. It also results in decrease in gain, and increase in beamwidth.

2.1.2: Factors causing element failure in antenna array:

i. **Physical Damage:** This is the major cause of antenna array failure. An over exploited use of an antenna array results in wear and tear resulting in element failure. Also while transporting an antenna array from one location to another, as in military applications, there is a chance of it getting damaged.

ii. **Environmental Effects:** An element in an antenna array may fail due to various environmental effects like temperature, corrosive environment etc. Example, the antenna array designed may get damaged when it is subjected to work under extreme environmental conditions. The elements in antenna array may also fail due to corrosion occurring because of salts and minerals, when installed in marines.

iii. **Ageing:** The antenna elements also fail because of ageing due to its continuous use of a long period of time. Example in air surveillance, the antenna arrays installed may fail because of its rigorous use for a long time.

There are many other reasons which may result in failure of antenna arrays, like, in warfare, during installation, unprecedented accidents, etc.

Following is the case showing the radiation pattern for a 35 element linear antenna array without failure, and with 11 elements (30% failure) failed. As evident, there is a considerable increase in the SLLs.

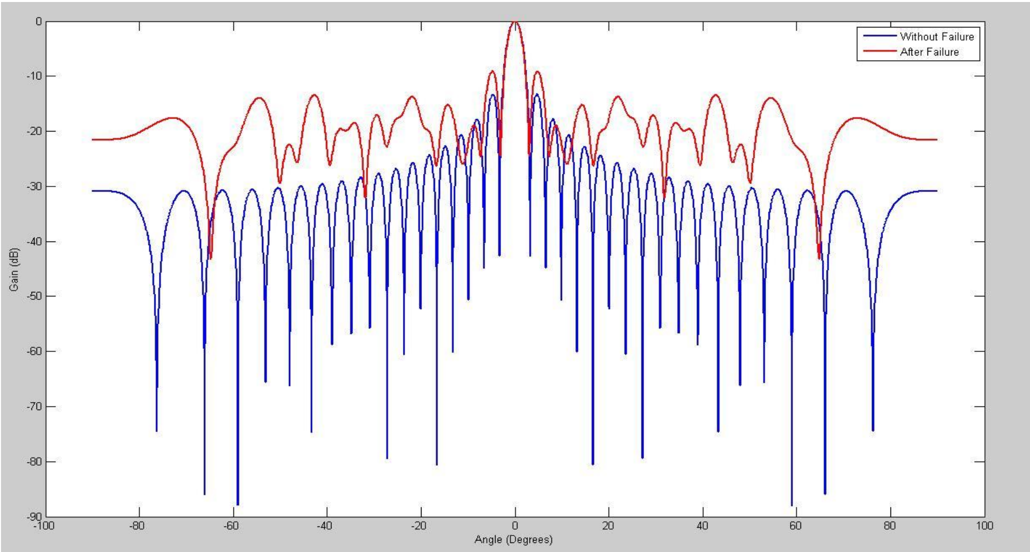

Figure 2.1: A typical radiation pattern with and without failure

2.2 TYPES OF ELEMENT FAILURES:

Element failure in an antenna array can be broadly classified into two categories:

- Distributed Failure
- Concentrated Failure

➢ Distributed Failure: In distributed failure, the elements of an antenna array fail at random locations, as shown in the figure below. This occurs more generally due to ageing and some of the environmental effects.

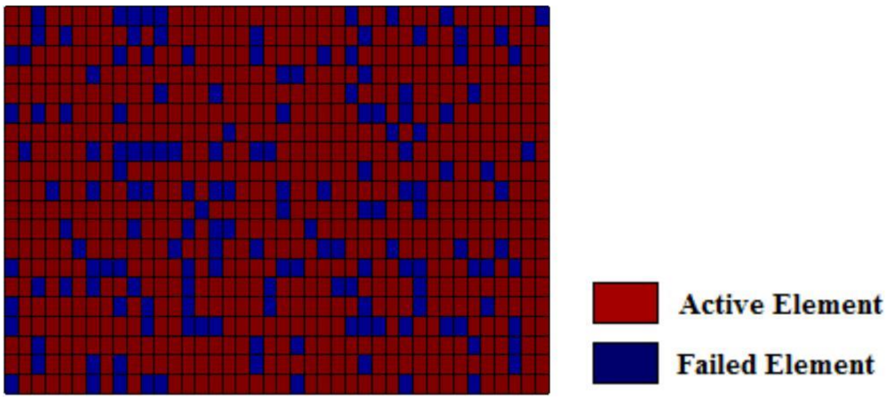

Figure 2.2: Distributed Failure

- Concentrated Failure: In concentrated failure, the elements of an antenna array fail in a random region as shown below. This generally occurs due to physical damage.

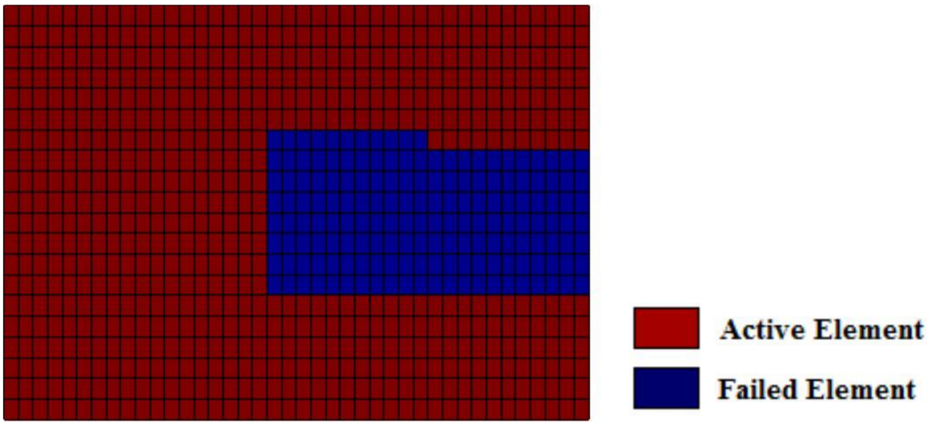

Figure 2.3: Concentrated Failure

CHAPTER 3

SEARCH OPTIMIZATION TECHNIQUES

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The basic principle of optimization is the efficient allocation of scarce resources. Optimization can be applied to any scientific or engineering discipline [1]. The aim of optimization is to find an algorithm, which solves a given class of problems. The various conventional optimization and search techniques available are discussed as follows:

3.1 RANDOM SEARCH:

Random search is an extremely basic method. It only explores the search space by randomly selecting solutions and evaluates their fitness. This is quite an unintelligent strategy, and is rarely used by itself. It doesn‘t take much effort to implement it, and an important number of evaluations can be done fairly quickly. For new unresolved problems, it can be useful to compare the results of a more advanced algorithm to those obtained just with a random search for the same number of evaluations.

Random search does have a few interesting qualities. However good the obtained solution may be, if it‘s not optimal one, it can be always improved by continuing the run of the random search algorithm for long enough. A random search never gets stuck in any point such as a local optimum. Furthermore, theoretically, if the search space is finite, random search is guaranteed to reach the optimal solution.

3.2 STOCHASTIC HILL CLIMBING:

Efficient methods exist for problems with well-behaved continuous fitness functions. These methods use a kind of gradient to guide the direction of search. Stochastic Hill Climbing is the simplest method of these kinds. Each iteration consists in choosing randomly a solution in the neighborhood of the current solution and retains this new solution only if it improves the fitness function. Stochastic Hill Climbing converges towards the optimal solution if the fitness function of the problem is continuous and has only one peak (unimodal function). On functions with many peaks (multimodal functions), the algorithm is likely to stop on the first peak it finds even if it is not the highest one. Once a peak is reached, hill climbing cannot progress anymore, and that is problematic when this point is a local optimum. Stochastic hill climbing usually starts from a random select point. A simple idea to avoid getting stuck on the first local optimal consists in repeating several hill climbs each time starting from a different randomly chosen point. This method is sometimes known as iterated hill climbing. By discovering different local optimal points, it gives more chance to reach the global optimum. It works well if there are not too any local optima in the search space. Stochastic hill climbing becomes less efficient when the fitness function has many peaks.

3.3 SIMULATED ANNEALING:

The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects, both are attributes of the material that depend on its thermodynamic free energy.

Simulated Annealing (SA) is a generic probabilistic metaheuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space. It is often used when the search space is discrete (e.g., all tours that visit a given set of cities). For certain problems, simulated annealing may be more efficient than exhaustive enumeration — provided that the goal is merely to find an acceptably good solution in a fixed amount of time, rather than the best possible solution.

As in the stochastic hill climbing, the iteration of the simulated annealing consists of randomly choosing a new solution in the neighborhood of the actual solution. If the fitness function of the new solution is better than the fitness function of the current one, the new solution is accepted as the new current solution. If the fitness function is not improved, the new solution is retained with a probability:

Where f (y) − f (x) is the difference of the fitness function between the new and the old solution.

3.4 EVOLUTIONARY COMPUTATION:

Evolutionary Algorithm (EA) is a subset of Evolutionary Computation (EC) which is a subfield of Artificial Intelligence (AI).

Evolutionary Computation (EC) is a general term for several computational techniques. Evolutionary Computation represents powerful search and optimization paradigm influenced by biological mechanisms of evolution: that of natural selection and genetic.

Evolutionary Algorithms (EAs) refers to Evolutionary Computational models using randomness and genetic inspired operations. EAs involve selection, recombination, random variation and competition of the individuals in a population of adequately represented potential solutions. The candidate solutions are referred as chromosomes or individuals.

Genetic Algorithms (GAs) represent the main paradigm of Evolutionary Computation. GAs simulate natural evolution, mimicking the processes that nature uses like Selection, Crosses over, Mutation and Accepting. GAs simulate the survival of the fittest among individuals over consecutive generation for solving a problem.

CHAPTER 4

GENETIC ALGORITHM

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PART – I

4.1 AN INTRODUCTION:

Charles Darwin stated the theory of natural evolution in the origin of species. Over several generations, biological organisms evolve based on the principle of natural selection ―survival of the fittest‖ to reach certain remarkable tasks. The perfect shapes of the albatross wring the efficiency and the similarity between sharks and dolphins and so on, are best examples of achievement of random evolution over intelligence. Thus, it works so well in nature, as a result it should be interesting to simulate natural evolution and to develop a method, which solves concrete, and search optimization problems [1].

In nature, an individual in population competes with each other for virtual resources like food, shelter and so on. Also in the same species, individuals compete to attract mates for reproduction. Due to this selection, poorly performing individuals have less chance to survive, and the most adapted or ―fit‖ individuals produce a relatively large number of offspring‗s. It can also be noted that during reproduction, a recombination of the good characteristics of each ancestor can produce ―best fit‖ offspring whose fitness is greater than that of a parent. After a few generations, species evolve spontaneously to become more and more adapted to their environment.

In 1975, Holland developed this idea in his book ―Adaptation in natural and artificial systems‖. He described how to apply the principles of natural evolution to optimization problems and built the first Genetic Algorithms. Holland‗s theory has been further developed and now Genetic Algorithms (GAs) stand up as a powerful tool for solving search and optimization problems. Genetic algorithms are based on the principle of genetics and evolution.

The power of mathematics lies in technology transfer: there exist certain models and methods, which describe many different phenomena and solve wide variety of problems. Gas are an example of mathematical technology transfer: by simulating evolution one can solve optimization problems from a variety of sources. Today, GAs are used to resolve complicated optimization problems, like, timetabling, job-shop scheduling, games playing.

4.2 BIOLOGICAL BACKGROUND:

The science that deals with the mechanisms responsible for similarities and differences in a species is called Genetics. The word ―genetics‖ is derived from the Greek word ―genesis‖ meaning ―to grow‖ or ―to become‖. The science of genetics helps us to differentiate between heredity and variations and seeks to account for the resemblances and differences due to the concepts of Genetic Algorithms and directly derived from natural heredity, their source and development. The concepts of Genetic Algorithms are directly derived from natural evolution. The main terminologies involved in the biological background of species are as follows:

4.2.1 The Cell

Every animal/human cell is a complex of many ―small‖ factories that work together. The center of all this is the cell nucleus. The genetic information is contained in the cell nucleus.

4.2.2 Chromosomes

All the genetic information gets stored in the chromosomes. Each chromosome is built of Dioxy Ribo Nucleic Acid (DNA). In humans, a chromosome exists in the form of pairs (23 pairs found). The chromosomes are divided into several parts called *genes*. Genes code the properties of species i.e., the characteristics of an individual. The possibilities of the genes for one property are called *allele* and a gene can take different alleles. For example, there is a gene for eye color, and all the different possible alleles are black, brown, blue and green (since no one has red or violet eyes). The set of all possible alleles present in a particular population forms a gene pool. This gene pool can determine all the different possible variations for the future generations. The size of the gene pool helps in determining the diversity of the individuals in the population. The set of all the genes of a specific species is called genome. Each and every gene has a unique position on the genome called locus. In fact, most living organisms store their genome on several chromosomes, but in the Genetic Algorithms (GAs), all the genes are usually stored on the same chromosomes. Thus chromosomes and genomes are synonyms with one other in GAs.

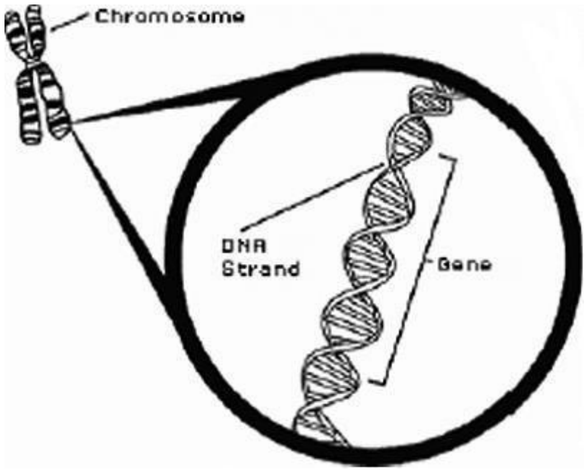


Figure 4.1: Model of Chromosome

4.2.3 Genetics:

For a particular individual, the entire combination of genes is called *genotype*. The *phenotype* describes the physical aspect of decoding a genotype to produce the phenotype. One interesting point of evolution is that selection is always done on the phenotype whereas the reproduction recombines genotype. Thus *morphogenesis* plays a key role between selection and reproduction. In higher life forms, chromosomes contain two sets of genes. This is known as *diploids*. In case of conflicts between two values of the same pair of genes, the dominant one will determine the phenotype whereas the other one, called *recessive*, will still be present and can be passed on to the offspring.

4.2.4 Reproduction

Reproduction of species via genetic information is carried out by,

- Mitosis
- Meiosis

In Mitosis the same genetic information is copied to new offspring. There is no exchange of information. This is a normal way of growing of multi cell structures, like organs.

Meiosis forms basis of sexual reproduction. When meiotic division takes place 2 gametes appears in the process. When reproduction occurs, these two gametes conjugate to a zygote which becomes the new individual. Thus in this case, the genetic information is shared between the parents in order to create new offspring.

4.2.5 Natural Selection

The origin of species is based on ―Preservation of favourable variations and rejection of unfavourable variations‖. The variation refers to the differences shown by the individual of a species and also by offspring‘s of the same parents. There are more individuals born than can survive, so there is a continuous struggle for life. Individuals with an advantage have a greater chance for survive i.e., the survival of the fittest.

The following Table 4.1 gives a list of different expressions, which are in common with natural evolution and genetic algorithm.

Natural Evolution	**Genetic Algorithm**
Chromosome	String
Gene	Feature or character
Allele	Feature value
Locus	String position
Genotype	Structure or coded string
Phenotype	Parameter set, a decoded structure

Table 4.1: Comparison of natural evolution and genetic algorithm terminology

4.3 WHAT IS GENETIC ALGORITHM?

Evolutionary computing was introduced in the 1960s by I. Rechenberg in the work ―Evolution strategies‖. This idea was then developed by other researches. Genetic Algorithms (GAs) was invented by John Holland and developed this idea in his book ―Adaptation in natural and artificial systems‖ in the year 1975. Holland proposed GA as a heuristic method based on ―Survival of the fittest‖. GA was discovered as a useful tool for search and optimization problems.

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‖ (i.e., minimizes the cost function).

4.3.1 Search Space

Most often one is looking for the best solution in a specific set of solutions. The space of all feasible solutions (the set of solutions among which the desired solution resides) is called search space (also state space). Each and every point in the search space represents one possible solution. Therefore each possible solution can be ―marked‖ by its fitness value, depending on the problem definition. With Genetic Algorithm one looks for the best solution among a number of possible solutions represented by one point in the search space i.e.; GAs are used to search the search space for the best solution e.g., minimum. The difficulties in this ease are the local minima and the starting point of the search.

4.3.2 Genetic Algorithms World

Genetic Algorithm raises a couple of important features. First it is a *stochastic algorithm*; randomness plays an essential role in genetic algorithms [7]. Both selection and reproduction needs random procedures. A second very important point is that genetic algorithms always consider a *population of solutions*. Some of the advantages of a GA include that is,

- Optimizes with continuous or discrete variables,
- Doesn‘t require derivative information,
- Simultaneously searches from a wide sampling of the cost surface,
- Deals with a large number of variables,
- Is well suited for parallel computers,
- Optimizes variables with extremely complex cost surfaces (they can jump out of a local minimum),
- Provides a list of optimum variables, not just a single solution,
- May encode the variables so that the optimization is done with the encoded variables, and
- Works with numerically generated data, experimental data, or analytical functions.

These advantages are intriguing and produce stunning results when traditional optimization approaches fail miserably.

4.3.3 A Simple Genetic Algorithm

An algorithm is a series of steps for solving a problem [1]. A genetic algorithm is a problem solving method that uses genetics as its model of problem solving. It‘s a search technique to find approximate solutions to optimization and search problems. The set of all the solutions that meet this form constitute the search space. The problem consists in finding out the solution that fits the best, i.e. the one with the most payoffs, from all the possible solutions. If it‘s possible to quickly enumerate all the solutions, the problem does not raise much difficulty. But, when the search space becomes large, enumeration is soon no longer feasible simply because it would take far too much time. In this it‘s needed to use a specific technique to find the optimal solution. Genetic Algorithms provides one of these methods. Practically they all work in a similar way, adapting the simple genetics to algorithmic mechanisms.

GA handles a population of possible solutions. Each solution is represented through a chromosome, which is just an abstract representation. Coding all the possible solutions into a chromosome is the first part. Also a set of reproduction operators has to be determined. Reproduction operators are applied directly on the chromosomes, and are used to perform mutations and recombinations over solutions of the problem. Appropriate representation and reproduction operators are really something determinant, as the behaviour of the GA is extremely dependant on it.

Selection is supposed to be able to compare each individual in the population. Selection is done by using a fitness function. Each chromosome has an associated value corresponding to the fitness of the solution it represents. The fitness should correspond to an evaluation of how good the candidate solution is. The optimal solution is the one, which maximizes the fitness function. Genetic Algorithms deal with the problems that maximize the fitness function. But, if the problem consists in minimizing a cost function, the adaptation is quite easy. Either the cost function can be transformed into a fitness function, for example by inverting it; or the selection can be adapted in such way that they consider individuals with low evaluation functions as better.

Reproduction is the process by which the genetic material in two or more parent is combined to obtain one or more offspring. In fitness evaluation step, the individual‘s quality is assessed. Mutation is performed to one individual to produce a new version of it where some of the original genetic material has been randomly changed. Selection process helps to decide which individuals are to be used for reproduction and mutation in order to produce new search points.

Once the reproduction and the fitness function have been properly defined, a Genetic Algorithm is evolved according to the same basic structure. It starts by generating an initial population of chromosomes. This first population must offer a wide diversity of genetic materials. The gene pool should be as large as possible so that any solution of the search space can be engendered. Generally, the initial population is generated randomly. Then, the genetic algorithm loops over an iteration process to make the population evolve.

Each of the iterations consists of the following steps:

- **SELECTION:** The first step consists in selecting individuals for reproduction. This selection is done randomly with a probability depending on the relative fitness of the individuals so that best ones are often chosen for reproduction than poor ones.
- **REPRODUCTION:** In the second step, offspring are bred by the selected individuals. For generating new chromosomes, the algorithm can use both recombination and mutation.
- **EVALUATION:** Then the fitness of the new chromosomes is evaluated.
- **REPLACEMENT:** During the last step, individuals from the old population are killed and replaced by the new ones.

The algorithm is stopped when the population converges toward the optimal solution. The basic genetic algorithm is as follows:

- [start] Genetic random population of n chromosomes (suitable solutions for the problem)
- [Fitness] Evaluate the fitness f(x) of each chromosome x in the population
- New population] Create a new population by repeating following steps until the New population is complete
  - [selection] select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to get selected).
  - [crossover] With a crossover probability, cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.
  - [Mutation] With a mutation probability, mutate new offspring at each locus (position in chromosome)
  - [Accepting] Place new offspring in the new population.
- [Replace] Use new generated population for a further sum of the algorithm.
- [Test] If the end condition is satisfied, stop, and return the best solution in current population.
- [Loop] Go to step2 for fitness evaluation.

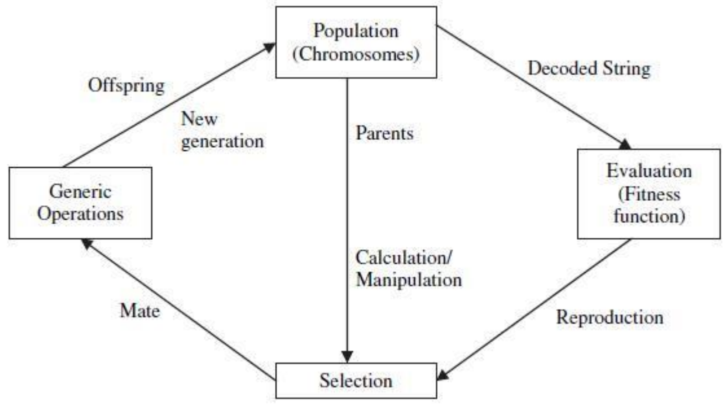


Figure 4.2: Genetic algorithm cycle

The flowchart showing the process of GA is as shown in Fig. 4.3.

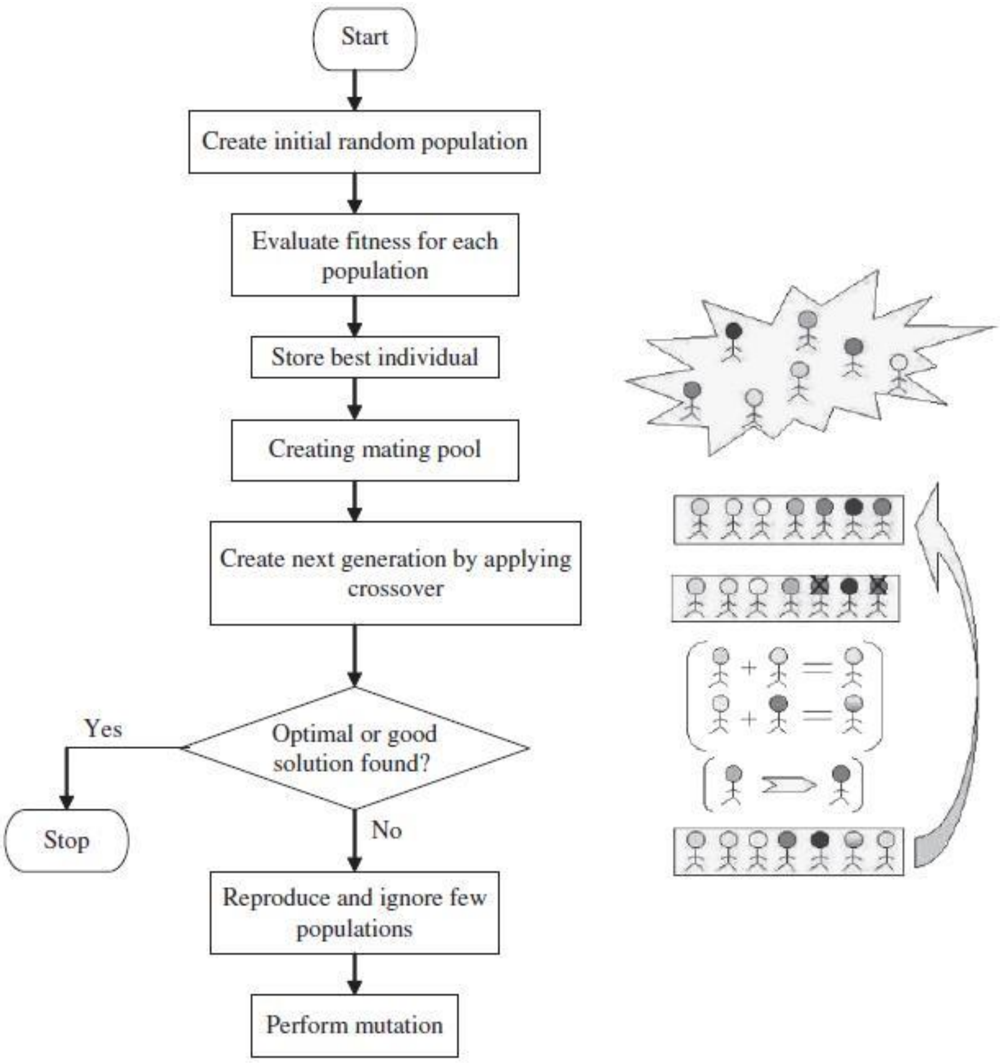


Figure 4.3: Flowchart of genetic algorithm

4.3.4 Comparison of Genetic Algorithm with Other Optimization Techniques

Genetic algorithm differs from conventional optimization techniques in following ways:

1. GAs operate with coded versions of the problem parameters rather than parameters themselves i.e., GA works with the coding of solution set and not with the solution itself.
2. Almost all conventional optimization techniques search from a single point but GAs always operate on a whole population of points(strings) i.e., GA uses population of solutions rather than a single solution for searching. This plays a major role to the robustness of genetic algorithms. It improves the chance of reaching the global optimum and also helps in avoiding local stationary point.
3. GA uses fitness function for evaluation rather than derivatives. As a result, they can be applied to any kind of continuous or discrete optimization problem. The key point to be performed here is to identify and specify a meaningful decoding function.
4. GAs use probabilistic transition operates while conventional methods for continuous optimization apply deterministic transition operates i.e., GAs does not use deterministic rules.

GA is not the only best way to solve every problem [7]. For instance, the traditional methods have been tuned to quickly find the solution of a well behaved convex analytical function of only a few variables. For such cases the calculus-based methods outperform the GA, quickly finding the minimum while the GA is still analyzing the costs of the initial population. For these problems the optimizer should use the experience of the past and employ these quick methods. However, many realistic problems do not fall into this category. In addition, for problems that are not overly difficult, other methods may find the solution faster than the GA. The large population of solutions that gives the GA its power is also its bane when it comes to speed on a serial computer—the cost function of each of those solutions must be evaluated. However, if a parallel computer is available, each processor can evaluate a separate function at the same time. Thus the GA is optimally suited for such parallel computations.

PART – II

4.4 ENCODING:

Before a genetic algorithm can be put to work on any problem, a method is needed to encode potential solutions to that problem in a form so that a computer can process [1].

- One common approach is to encode solutions as binary strings: sequences of 1's and 0's, where the digit at each position represents the value of some aspect of the solution.

  Example:

  A Gene represents some data. A chromosome is an array of genes. In binary

  form a Gene looks like: (11100010)

  a Chromosome looks like: Gene1 Gene2 Gene3 Gene4

  (11000010, 00001110, 001111010, 10100011)

  A chromosome should in some way contain information about solution which it represents; it thus requires encoding. The most popular way of encoding is a binary string like:

  Chromosome 1: 1101100100110110

  Chromosome 2: 1101111000011110

  Each bit in the string represents some characteristics of the solution.

- There are many other ways of encoding, e.g., encoding values as integer or real numbers or some permutations and so on.
- The virtue of these encoding methods depends on the problem to work on.

4.4.1 Binary Encoding

Binary encoding is the most common to represent information contained. In genetic algorithms, it was first used because of its relative simplicity.

- In binary encoding, every chromosome is a string of bits : 0 or 1, like

Chromosome 1: 1 0 1 1 0 0 1 0 1 1 0 0 1 0 1 0 1 1 1 0 0 1 0 1
Chromosome 2: 1 1 1 1 1 1 1 0 0 0 0 0 1 1 0 0 0 0 0 1 1 1 1 1

- Binary encoding gives many possible chromosomes even with a small number of alleles i.e. possible settings for a trait (features).
- This encoding is often not natural for many problems and sometimes corrections must be made after crossover and/or mutation.

4.4.2 Value Encoding

The Value encoding can be used in problems where values such as real numbers are used. Use of binary encoding for this type of problems would be difficult.

- In value encoding, every chromosome is a sequence of some values.
- The Values can be anything connected to the problem, such as: real numbers, characters or objects.

Examples:

Chromosome A 1.2324 5.3243 0.4556 2.3293 2.4545
Chromosome B ABDJEIFJDHDIERJFDLDFLFEGT
Chromosome C (back), (back), (right), (forward), (left)

- Value encoding is often necessary to develop some new types of crossovers and mutations specific for the problem.

4.4.3 Permutation Encoding

Permutation encoding can be used in ordering problems, such as traveling salesman problem or task ordering problem.

1. In permutation encoding, every chromosome is a string of numbers that represent a position in a sequence.

   Chromosome A 1 5 3 2 6 4 7 9 8

   Chromosome B 8 5 6 7 2 3 1 4 9

2. Permutation encoding is useful for ordering problems. For some problems, crossover and mutation corrections must be made to leave the chromosome consistent.

4.4.4 Tree Encoding

Tree encoding is used mainly for evolving programs or expressions.
For genetic programming:

- In tree encoding, every chromosome is a tree of some objects, such as functions or commands in programming language.
- Tree encoding is useful for evolving programs or any other structures that can be encoded in trees.
- The crossover and mutation can be done relatively easy way.

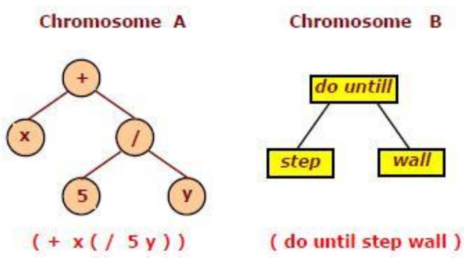


Figure 4.4: Example of Tree encoding

4.5 SELECTION:

Selection is the process of choosing two parents from the population for crossing [1]. After deciding on an encoding, the next step is to decide how to perform selection i.e., how to choose individuals in the population that will create offspring for the next generation and how many offspring each will create. The purpose of selection is to emphasize fitter individuals in the population in hopes that their off springs have higher fitness. Chromosomes are selected from the initial population to be parents for reproduction.

Selection is a method that randomly picks chromosomes out of the population according to their evaluation function. The higher the fitness function, the more chance an individual has to be selected. The selection pressure is defined as the degree to which the better individuals are favoured. The higher the selection pressured, the more the better individuals are favoured. This selection pressure drives the GA to improve the population fitness over the successive generations.

The convergence rate of GA is largely determined by the magnitude of the selection pressure, with higher selection pressures resulting in higher convergence rates. In addition to providing selection pressure, selection schemes should also preserve population diversity, as this helps to avoid premature convergence.

4.5.1 Roulette Wheel Selection

The population must first be sorted for roulette wheel selection. Each chromosome is assigned a probability of selection on the basis of either its rank in the sorted population or its cost. Rank order selection is the easiest implementation of roulette wheel selection.

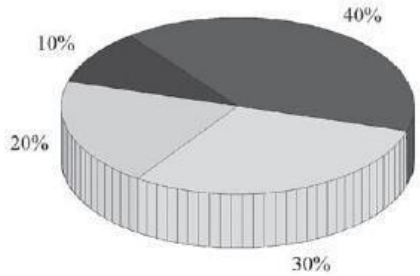


Figure 4.5: Roulette wheel probabilities for four parents in the mating pool.

The roulette wheel for a selection pool of four parents is shown in Figure 5.5. Chromosomes with low costs have a higher percent chance of being selected than do chromosomes with higher costs. In this case, the first or best chromosome has a 40% chance of being selected. As more parents are added, the percent chance of a chromosome being selected changes.

It is possible to develop a roulette wheel on the basis of the costs associated with the chromosomes. There are several problems related to this approach:

1. The roulette wheel must be recomputed every generation.
2. If the mutation rate is low, then in later generations all the chromosomes will have approximately the same probability of selection.
3. The costs must be normalized in order to develop the probabilities. The normalization is arbitrary.

4.5.2 Tournament Selection:

A second approach to finding parents randomly selects two small groups of chromosomes from the mating pool (usually two or three per group). The chromosome with the lowest cost in each group becomes a parent. Enough of these tournaments are held to generate the required number of parents. The tournament repeats for every parent needed. Tournament selection works well with thresholding, because the population never needs sorting. Sort speed becomes an issue only with large population sizes. Figure 5.6 diagrams the tournament selection process when three chromosomes are selected for each tournament.

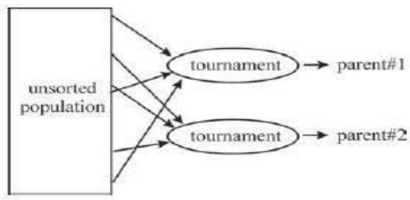


Figure 4.6: Tournament selection

<u>Elitism</u>

The first best chromosome or the few best chromosomes are copied to the new population [2], [7]. The rest is done in a classical way. Such individuals can be lost if they are not selected to reproduce or if crossover or mutation destroys them. This significantly improves the GA‘s performance.

4.5.3 Best-Mate-Worst (BMW):

BMW effectively spreads the superior genetic material in the population [6]. It is maximally disruptive, but weaker individuals with any desirable traits do get a chance to produce Offsprings with stronger partners. In BMW, the best gets to mate with the worst, and second-best with the second-worst individual. Thus it is inclined to reduce the difference in fitnesses between the best and the worst individuals, with a low bias for an elitist group.

4.5.4 Adjacent-Fitness-Pairing (AFP):

AFP mates two individuals with adjacent fitnesses. Thus the best pairs with the second-best, the third-best mates with the fourth-best and so forth. It is highly conservative of genetic information but may result in premature convergence. However, AFP ensures the union of strong individuals whose Offsprings may prove to be fitter than their parents. AFP does not allow any individual to breed twice. Moreover, the population that it works on stays static throughout the mating process.

4.5.5 Emperor-Selective (EMS):

The best individual in the population gets to mate with every other even sample in the population, as shown in Fig. 4.7. If one or more near-solutions are added to an initial population of random individuals, EMS usually yields the best chromosome. It is the only method that allows the fittest individual to procreate freely with practically the rest of the population.

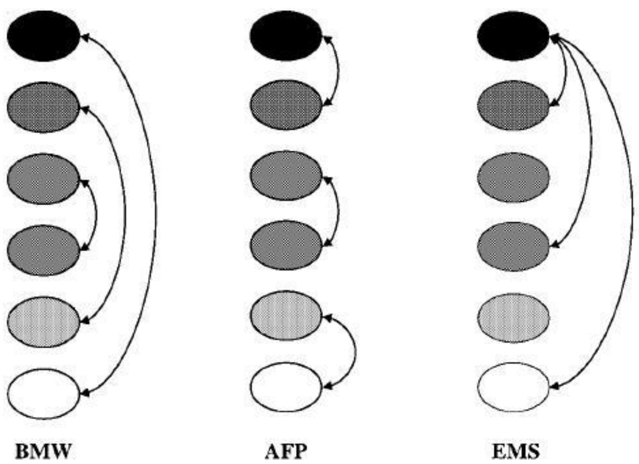


Figure 4.7: Three selection schemes, darker shade represents higher fitness level.

4.6 CROSS-OVER:

Crossover is the process of taking two parent solutions and producing from them a child [1]. After the selection (reproduction) process, the population is enriched with better individuals. Reproduction makes clones of good strings but does not create new ones. Crossover operator is applied to the mating pool with the hope that it creates a better offspring.

4.6.1 Single Point Crossover

The traditional genetic algorithm uses single point crossover, where the two mating chromosomes are cut once at corresponding points and the sections after the cuts exchanged. Here, a cross-site or crossover point is selected randomly along the length of the mated strings and bits next to the cross-sites are exchanged. If appropriate site is chosen, better children can be obtained by combining good parents else it severely hampers string quality. The below Fig. 4.8 illustrates single point crossover.

Figure 4.8: Single Point Crossover

4.6.2 Two Point Crossover

Apart from single point crossover, many different crossover algorithms have been devised, often involving more than one cut point. It should be noted that adding further crossover points reduces the performance of the GA. The problem with adding additional crossover points is that building blocks are more likely to be disrupted. However, an advantage of having more crossover points is that the problem space may be searched more thoroughly. In two-point crossover, two crossover points are chosen and the contents between these points are exchanged between two mated parents.

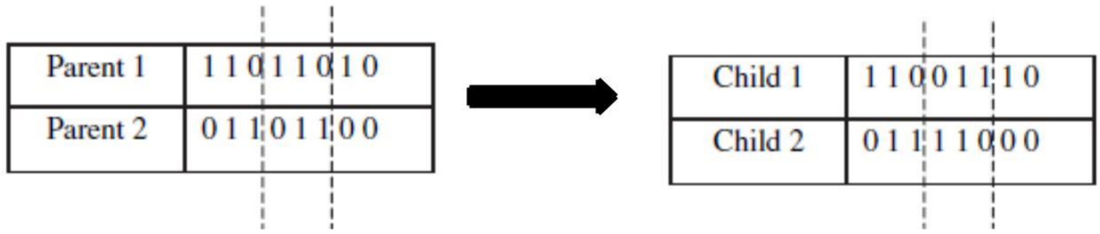


Figure 4.9: Two-point Crossover

4.6.3 Uniform Crossover:

Uniform crossover is quite different from the N-point crossover. Each gene in the offspring is created by copying the corresponding gene from one or the other parent chosen according to a random generated binary crossover mask of the same length as the chromosomes. Where there is a 1 in the crossover mask, the gene is copied from the first parent, and where there is a 0 in the mask the gene is copied from the second parent. A new crossover mask is randomly generated for each pair of parents. Offsprings, therefore contain a mixture of genes from each parent. The number of effective crossing point is not fixed, but will average L/2 (where L is the chromosome length).

In Fig. 4.10, new children are produced using uniform crossover approach. It can be noticed, that while producing child 1, when there is a 1 in the mask, the gene is copied from the parent 1 else from the parent 2. On producing child 2, when there is a 1 in the mask, the gene is copied from parent 2, when there is a 0 in the mask; the gene is copied from the parent 1.

Parent 1	1 0 1 1 0 0 1 1
Parent 2	0 0 0 1 1 0 1 0
Mask	1 1 0 1 0 1 1 0
Child 1	1 0 0 1 1 0 1 0
Child 2	0 0 1 1 0 0 1 1

Figure 4.10: Uniform crossover

4.6.4 Mid-point crossover:

Given two parents where X and Y represent a floating point number, [15]:

- Parent 1: X
- Parent 2: Y
- Offspring: (X+Y)/2

If a chromosome contains more than one gene, then this operator can be applied to each gene with a fixed probability.

4.6.5 Flat Crossover (BLX-0.0):

Flat crossover was developed by Radcliffe (1991). Given two parents where X and Y represent a floating point number:

- Parent 1: X
- Parent 2: Y
- Offspring: random(X,Y)

If a chromosome contains more than one gene then this operator can be applied to each gene with a certain probability.

4.6.6 BLX-α:

Developed by Eshelman & Schaffer (1992). Given two parents where X and Y represent a floating point number, and where X < Y:

- Parent 1: X
- Parent 2: Y
- Let $\Delta = \alpha(Y\text{-}X)$, where $\alpha = 0.5$ generally
- Offspring: random($X\text{-}\Delta$, $Y+\Delta$)

If a chromosome contains more than one gene then this operator can be applied to each gene with a probability of $P_{blx\text{-}\alpha}$.

4.7 MUTATION:

After a crossover is performed, mutation takes place [1]. Mutation is used to maintain genetic diversity from one generation of a population of chromosomes to the next.

Mutation occurs during evolution according to a user-definable mutation probability, usually set to fairly low value. Mutation alters one or more gene values in a chromosome from its initial state. This can result in entirely new gene values being added to the gene pool. With the new gene values, the genetic algorithm may be able to arrive at better solution than was previously possible.

Mutation is an important part of the genetic search, helps to prevent the population from stagnating at any local optima. Mutation is intended to prevent the search falling into a local optimum of the state space.

4.7.1 Flipping:

Flipping of a bit involves changing 0 to 1 and 1 to 0 based on a mutation chromosome generated.

The Fig. 4.11 explains mutation-flipping concept. A parent is considered and a mutation chromosome is randomly generated. For a 1 in mutation chromosome, the corresponding bit in parent chromosome is flipped (0 to 1 and 1 to 0) and child chromosome is produced. In the above case, there occurs 1 at 3 places of mutation chromosome, the corresponding bits in parent chromosome are flipped and child is generated.

Parent	1 0 1 1 **0** 1 0 1
Mutation chromosome	**1** 0 0 0 **1** 0 0 **1**
Child	**0** 0 1 1 **1** 1 0 **0**

Figure 4.11: Mutation-Flipping

4.7.2 Interchanging:

Two random positions of the string are chosen and the bits corresponding to those positions are interchanged.

Parent	1 **0** 1 1 0 **1** 0 1
Child	1 **1** 1 1 0 **0** 0 1

Figure 4.12: Interchanging

4.7.3 Reversing:

A random position is chosen and the bits next to that position are reversed and child chromosome is produced.

Parent	1 0 1 1 0 1 0 1
Child	1 0 1 1 0 1 1 0

Figure 4.13: Reversing

<u>Mutation Rate:</u>

The mutation rate is the portion of bits or values within a population that will be changed [2].

<u>Mutation Probability:</u>

The important parameter in the mutation technique is the mutation probability (Pm). The mutation probability decides how often parts of chromosome will be mutated. If there is no mutation, offspring are generated immediately after crossover (or directly copied) without any change. If mutation is performed, one or more parts of a chromosome are changed. Mutation generally prevents the GA from falling into local extremes. Mutation should not occur very often, because then GA will in fact change to random search [1].

4.8 REPLACEMENT:

Replacement is the last stage of any breeding cycle [1]. Two parents are drawn from a fixed size population, they breed two children, but not all four can return to the population, so two must be replaced i.e., once off springs are produced, a method must determine which of the current members of the population, if any, should be replaced by the new solutions. This technique is used to decide which individual stay in a population and which are replaced in on a par with the selection in influencing convergence.

4.8.1 Random Replacement

The children replace two randomly chosen individuals in the population. The parents are also candidates for selection. This can be useful for continuing the search in small populations, since weak individuals can be introduced into the population.

4.8.2 Weak Parent Replacement

In weak parent replacement, a weaker parent is replaced by a strong child. With the four individuals only the fittest two, parent or child, return to population. This process improves the overall fitness of the population when paired with a selection technique that selects both fit and weak parents for crossing, but if weak individuals and discriminated against in selection the opportunity will never raise to replace them.

4.8.3 Both Parents

Both parents replacement is simple. The child replaces the parent. In this case, each individual only gets to breed once. As a result, the population and genetic material moves around but leads to a problem when combined with a selection technique that strongly favors fit parents: the fit breed and then are disposed of.

4.9 SEARCH TERMINATION (CONVERGENCE CRITERIA):

In short, the various stopping condition [1] are listed as follows:

- **Maximum generations**–The genetic algorithm stops when the specified number of generations has evolved.

- **Elapsed time**–The genetic process will end when a specified time has elapsed.
  Note: If the maximum number of generation has been reached before the specified time has elapsed, the process will end.

- **No change in fitness**–The genetic process will end if there is no change to the population‘s best fitness for a specified number of generations.
  Note: If the maximum number of generation has been reached before the specified number of generation with no changes has been reached, the process will end.

- **Stall generations**–The algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length stall generations.

- **Stall time limit**–The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit. The termination or convergence criterion finally brings the search to a halt. The following are the few methods of termination techniques.

The termination or convergence criterion finally brings the search to a halt.

CHAPTER 5

GA FOR ELEMENT FAILURE MITIGATION

IN

ANTENNA ARRAYS

CHAPTER 5: GA FOR ELEMENT FAILURE MITIGATION IN ANTENNA ARRAYS

5.1 CASE STUDY:

- Following configurations of antenna arrays are considered for analysis:
  - Linear antenna array
  - Planar antenna array
    1. Rectangular
    2. Hexagonal
    3. Rhombic

- The percentages of failure induced in the analysis are: 10%, 20%, and 50%, for both distributed and concentrated types of failures.
- The simulations are obtained using MATLAB software.

5.2 OBJECTIVE AND PRINCIPLE:

- The main objective is to analyse the pattern of flawed antenna array, and to revive the pattern by suppressing the side-lobe levels.
- The principle used to revive the pattern is to use Genetic Algorithm as an optimization technique on the antenna weights to mitigate the effect of antenna element failures.

5.3 GA ON LINEAR ANTENNA ARRAY:

5.3.1 Specifications of Linear Antenna Array:

A linear antenna array of 35 elements is considered for the analysis. The radiation pattern is obtained for the polar location angle of 0°. The individual element spacing is taken as $\lambda/2$, where λ is the wavelength in meters. The radiation patterns plotted are normalised.

5.3.2 Specifications of Planar Antenna Array:

Planar antenna arrays of dimension [21 x 41] are considered for the analysis. The radiation patterns are obtained for an azimuthal angle of 60° and elevation angle of 30°. The individual element spacing is taken as $\lambda/2$, where λ is the wavelength in meters. The radiation patterns plotted are normalised.

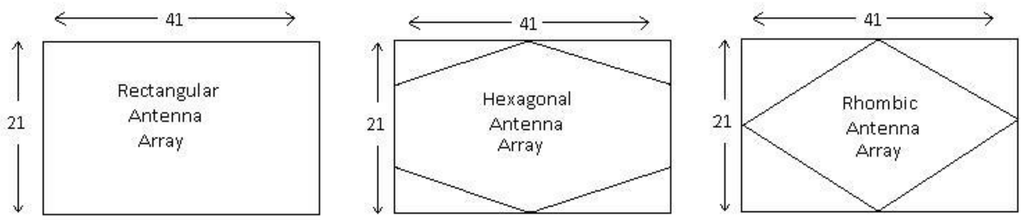


Figure 5.1: Antenna Arrays

5.3.2 Stages:

1. Initially, a reference pattern using Taylor weights is generated which is the close approximation to the original pattern i.e., without failure. The Taylor weights are obtained by normalizing the Taylor window. Then, these Taylor weights are used to obtain the reference pattern using the received signal assuming all elements are active.
2. Random failure is induced, either of distributed form or concentrated form on different shapes of antennas with various percentages of failures considered for analysis.

3. After inducing failure, the antenna elements are turned non-active on those locations. These non-active elements produce ‗0' output signal. The deformed pattern is obtained and analysed.

4. Now Genetic Algorithm is applied.

   4.1 Parameter specifications:

   - **Gene:** Individual antenna elements,
   - **Chromosome:** Entire antenna array
   - **Population:** Number of antenna arrays with random amplitude weighting
   - **Cost Function:** Ratio of new generations from GA to side-lobe levels of Taylor reference.
   - **Selection Methodology:** Emperor Selection (EMS) Method
   - **Cross-over Methodology:** BLX-α
   - **Mutation Methodology:** Gaussian mutation with a fixed mutation rate

   4.2 Procedure:

   a. Using above specifications, an initial random population of amplitude weights is generated, and the fitness value of each chromosome is determined.

   [Fitness value: *side-lobe level of each chromosome*]

   b. For faster convergence, the least fit chromosome is replaced by Taylor weight.
   c. Now a sorted population is considered for selection of two parent chromosomes for cross-over.
   d. Parent chromosomes are selected based on EMS method for cross-over.
   e. Cross-over is performed using BLX-α method, by considering α=0.5, and a new offspring population is generated. The value of each gene (amplitude weights) is bounded within the intervals 0 and 1.
   f. Mutation is performed on the new offspring population using Gaussian Method, and fitness value of each mutated chromosome is evaluated.

g. The fitness function of mutated Offsprings is compared with that of parent population and if the value of offspring fitness function is better than parent fitness function value, offspring population replaces parent population for the next generation considering elitism. However, if the parent fitness function value is better, then the offspring population is discarded, and the parent population is forwarded for the next generation.
h. The above process is repeated until the fitness value does not improve for continuous 25 generation (stall generations).

5. The weights produced after the termination criteria of GA will be optimum and are used to obtain corrected pattern.

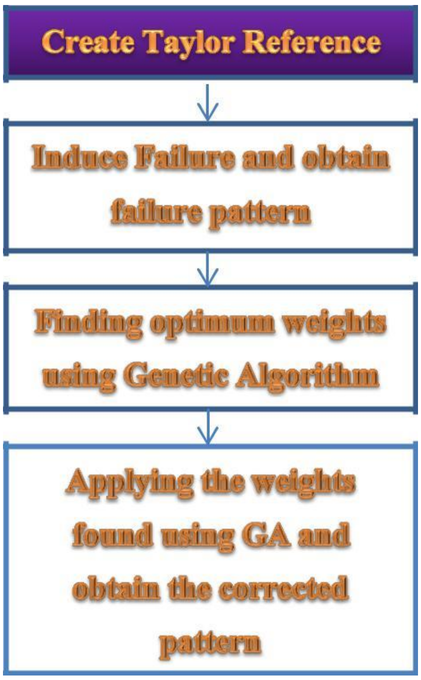


Figure 5.2: Flow of Approach

CHAPTER 6

RESULTS

CHAPTER 6: RESULTS

6.1 LINEAR ANTENNA ARRAY:

6.1.1 Distributed Failure – 10%:

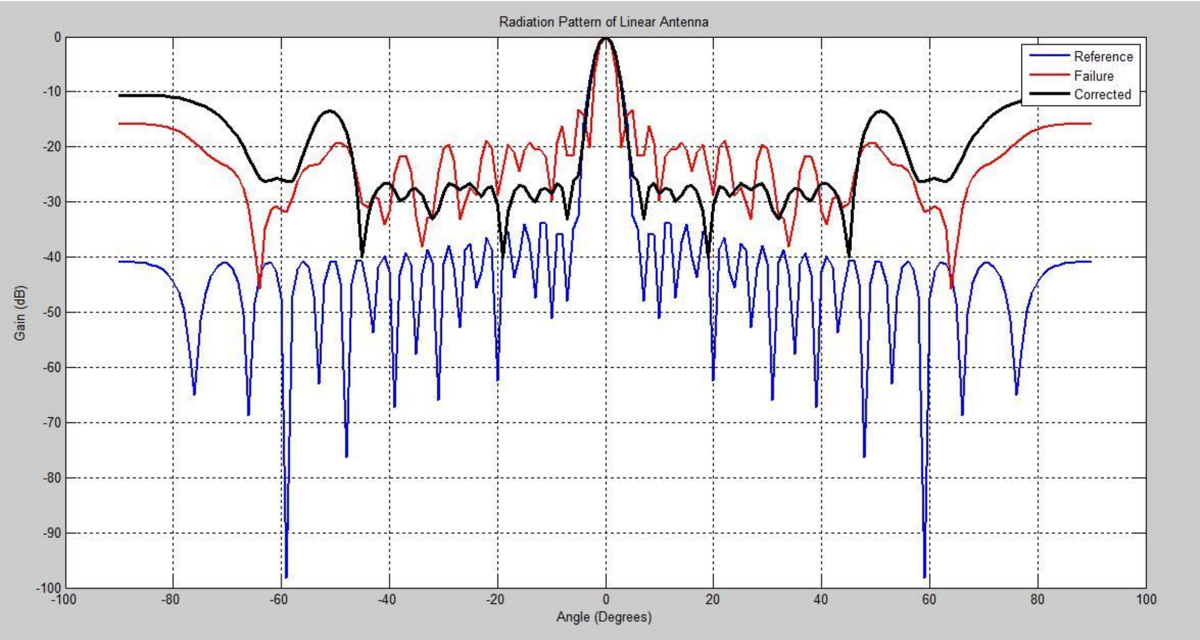


Figure 6.1: Linear antenna array patterns with 10% distributed failure.

Results for 10% distributed failure in case of linear array are presented [figure 6.1]. Number of antenna failed was 4. The pattern of reference, failure and corrected are plotted. The gain of first left SLL and right SLL are -13.2197dB and -13.2197dB respectively. The mean and σ of SLLs -24.6621dB and 5.8012dB respectively showed a rise, indicating discrepancy. After correction, the first SLL and right SLL were -26.6584dB and -26.6584dB respectively, although the beam width was spread. The difference in beamwidth was within 1°. The mean and σ -28.9383dB and 2.8432dB respectively also showed improvement within 45° and -45°. *Appendix A* shows the computed results.

6.1.2 Distributed Failure – 20%:

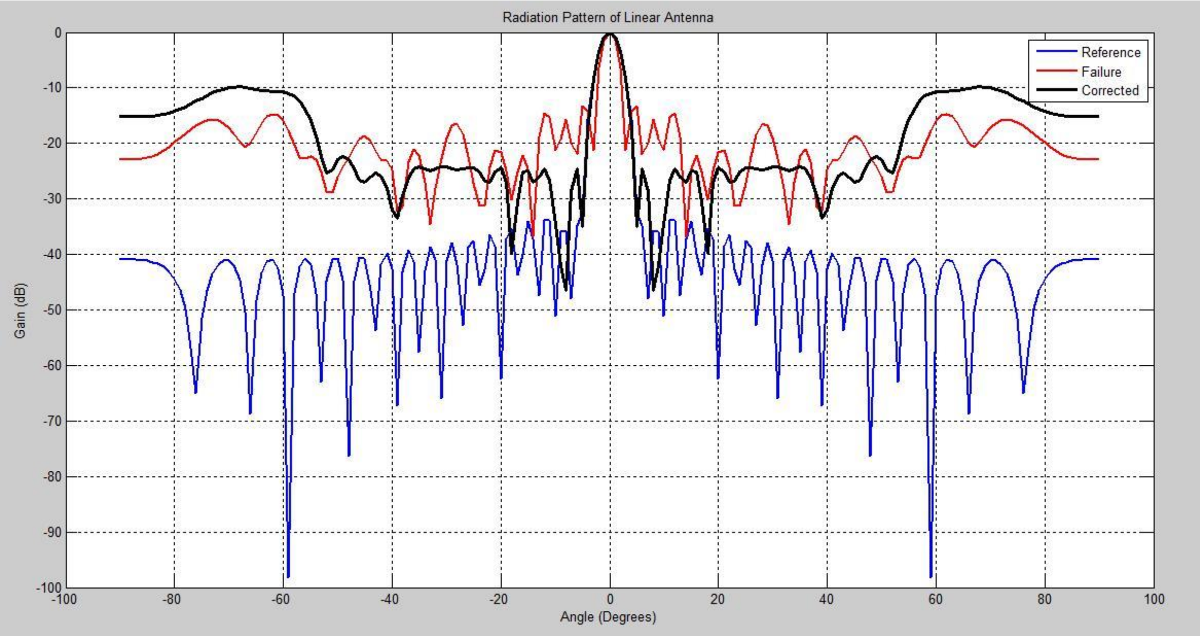


Figure 6.2: Linear antenna array patterns with 20% distributed failure.

Results for 20% distributed failure in case of linear array are presented [figure 6.2]. Number of antenna failed was 7. The pattern of reference, failure and corrected are plotted. The gain of first left SLL and right SLL are -13.254dB and -13.254dB respectively. The mean and σ of SLLs -22.868dB and 5.6159dB respectively showed a rise, indicating discrepancy. After correction, the first SLL and right SLL were -24.5006dB and -24.5006dB respectively, although the beam width was spread. The difference in beamwidth was within 6°. The mean and σ -27.5954dB and 5.0907dB respectively also showed improvement within 45° and -45°. *Appendix A* shows the computed results.

6.1.3 Distributed Failure – 50%:

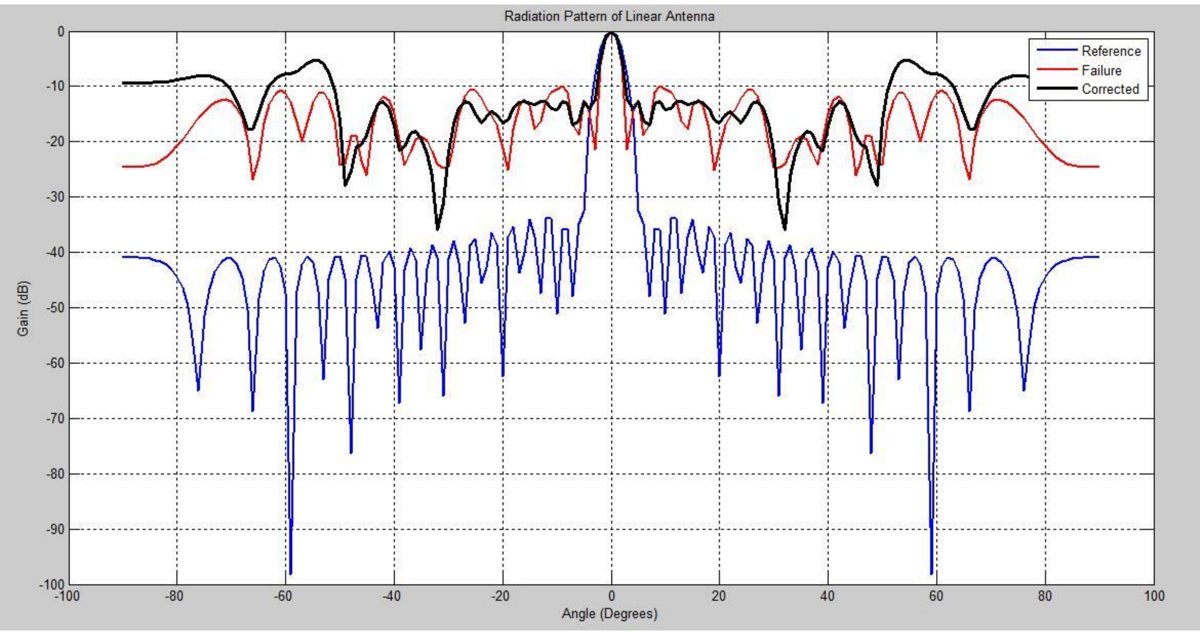


Figure 6.3: Linear antenna array patterns with 50% distributed failure.

Results for 50% distributed failure in case of linear array are presented [figure 6.3]. Number of antenna failed was 18. The pattern of reference, failure and corrected are plotted. The gain of first left SLL and right SLL are -12.558dB and -12.558dB respectively. The mean and σ of SLLs -16.5511dB and 4.6853dB respectively showed a rise, indicating discrepancy. After correction, the first SLL and right SLL were -12.7693dB and -12.7693dB respectively, although the beam width was spread. The difference in beamwidth was within 10°. The mean and σ -16.7129dB and 5.0262dB respectively also showed improvement within 45° and -45°. *Appendix A* shows the computed results.

6.1.4 Concentrated Failure – 10%:

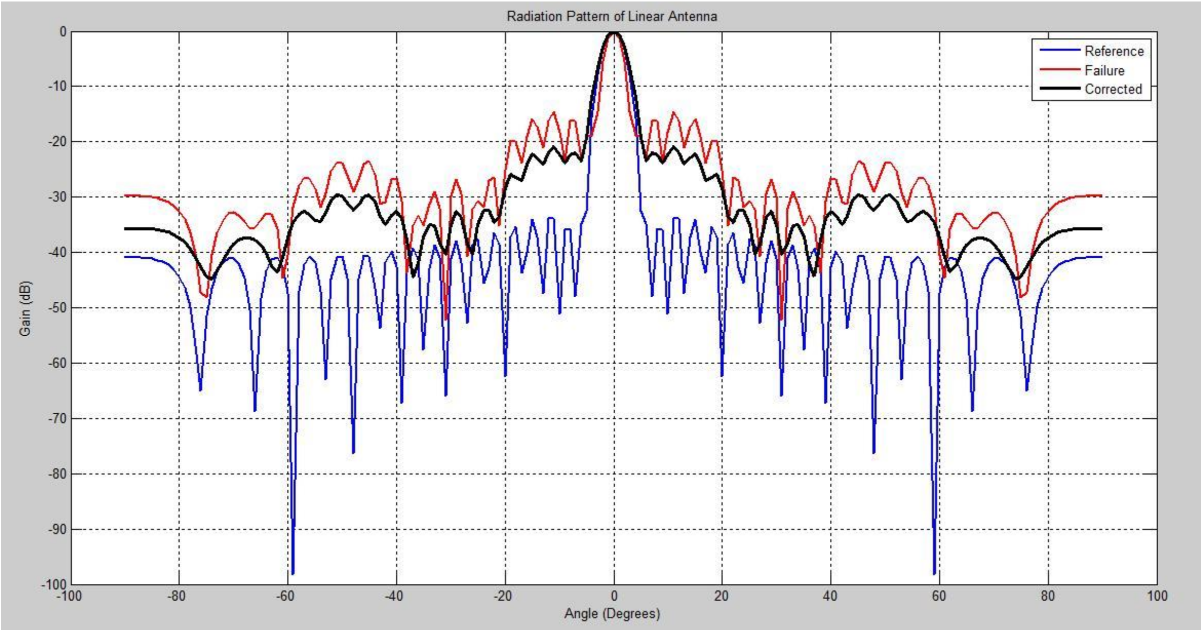


Figure 6.4: Linear antenna array patterns with 10% concentrated failure.

Results for 10% concentrated failure in case of linear array are presented [figure 6.4]. Number of antenna failed was 4. The pattern of reference, failure and corrected are plotted. The gain of first left SLL and right SLL are -16.2114dB and -16.2114dB respectively. The mean and σ of SLLs -27.2928dB and 8.1254dB respectively showed a rise, indicating discrepancy. After correction, the first SLL and right SLL were -22.0535dB and -22.0535dB respectively, although the beam width was spread. The difference in beamwidth was within 1°. The mean and σ -31.3046dB and 6.3979dB respectively also showed improvement within 45° and -45°. *Appendix A* shows the computed results.

6.1.5 Concentrated Failure – 20%:

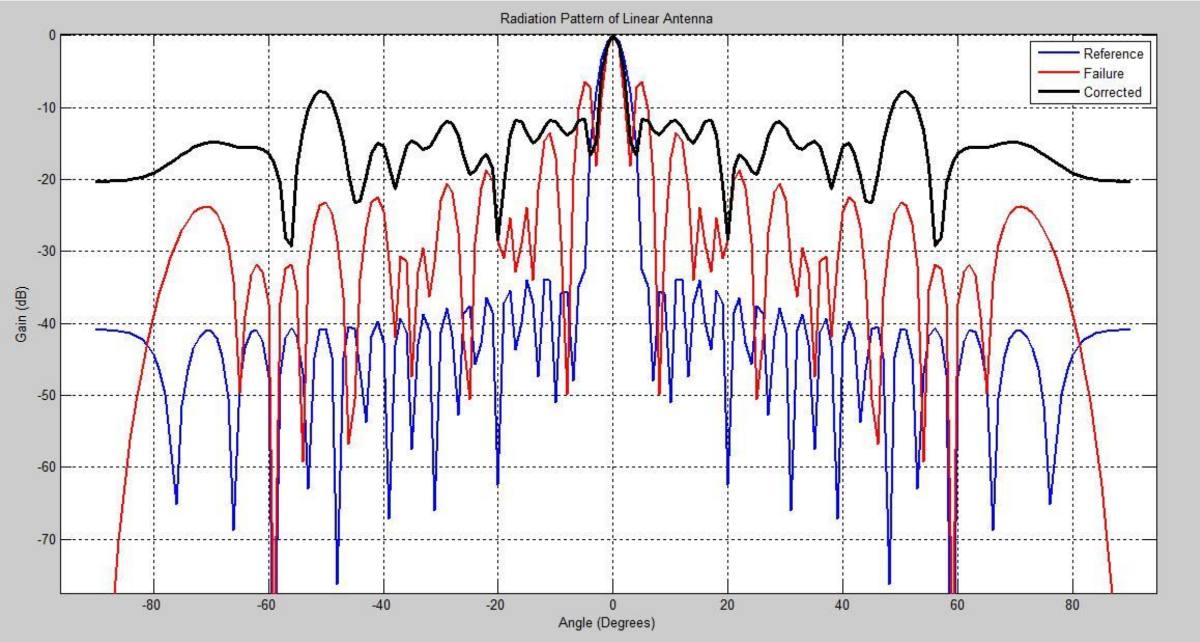


Figure 6.5: Linear antenna array patterns with 20% concentrated failure.

Results for 20% concentrated failure in case of linear array are presented [figure 6.5]. Number of antenna failed was 7. The pattern of reference, failure and corrected are plotted. The gain of first left SLL and right SLL are -6.4664dB and -6.4664dB respectively. The mean and σ of SLLs -27.727dB and 10.8788dB respectively showed a rise, indicating discrepancy. After correction, the first SLL and right SLL were -11.6941dB and -11.6941dB respectively, although the beam width was spread. The difference in beamwidth was within 6°. The mean and σ -15.7758dB and 3.6406dB respectively also showed improvement within 45° and -45°. *Appendix A* shows the computed results.

6.1.6 Concentrated Failure – 50%:

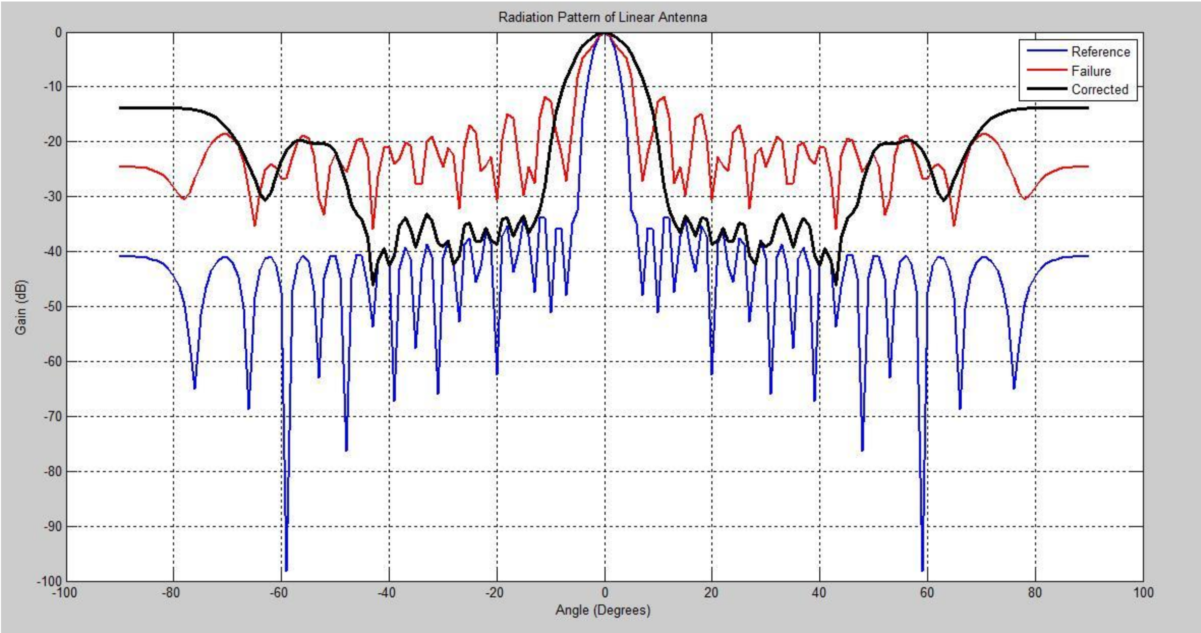


Figure 6.6: Linear antenna array patterns with 50% concentrated failure.

Results for 50% concentrated failure in case of linear array are presented [figure 6.6]. Number of antenna failed was 18. The pattern of reference, failure and corrected are plotted. The gain of first left SLL and right SLL are -11.8131dB and -11.8131dB respectively. The mean and σ of SLLs -22.2558dB and 5.1193dB respectively showed a rise, indicating discrepancy. After correction, the first SLL and right SLL were -33.5536dB and -33.5536dB respectively, although the beam width was spread. The difference in beamwidth was within 10°. The mean and σ -37.4331dB and 3.1849dB respectively also showed improvement within 45° and -45°. *Appendix A* shows the computed results.

6.2 RECTANGULAR ANTENNA ARRAY:

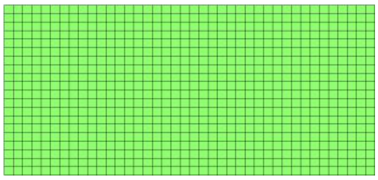
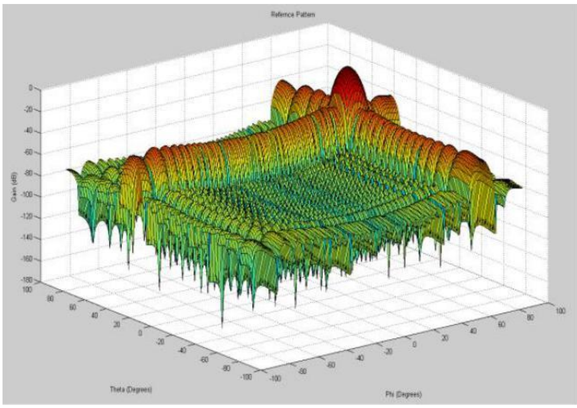
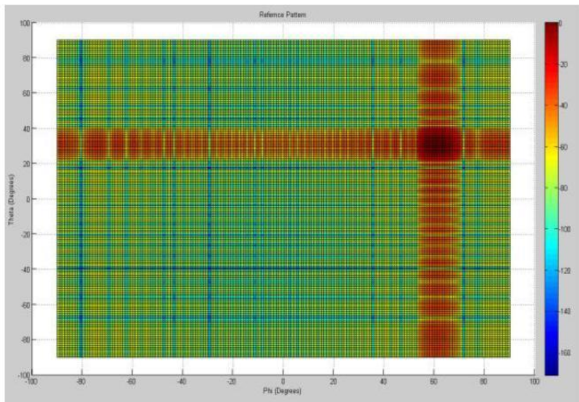


Figure 6.7: Rectangular array without failure

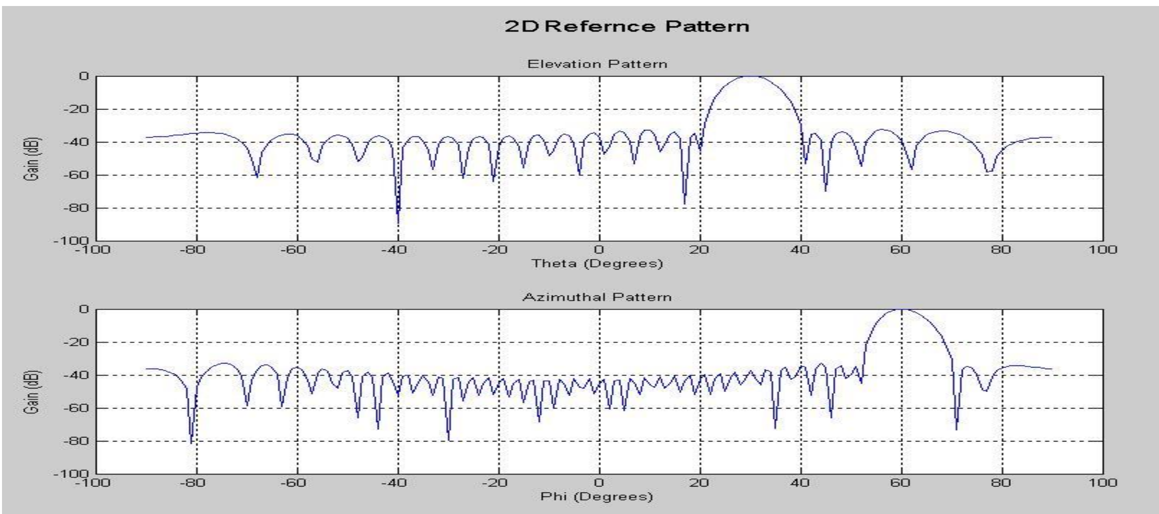
6.2.1 Taylor Reference:



(a)



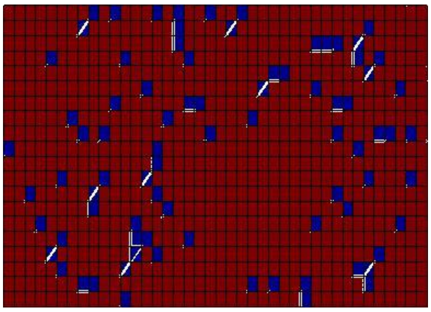
(b)



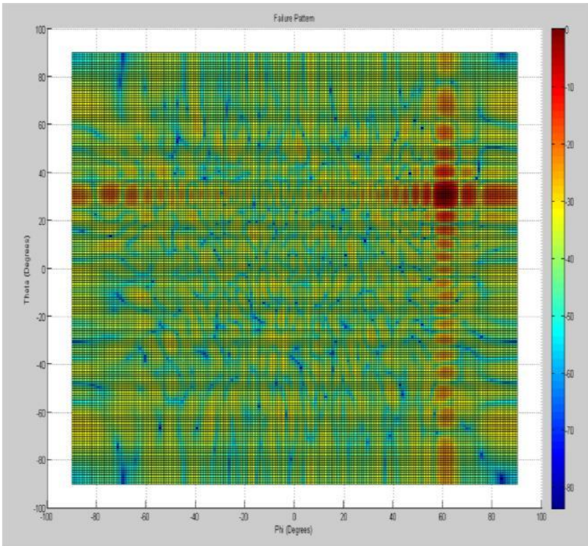
(c)

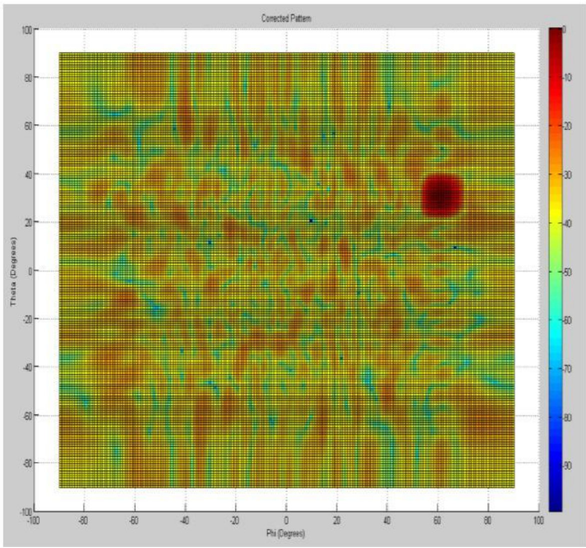
Figure 6.8: (a) Three-Dimensional Reference Pattern, (b) XY view (top view), (c) Two-Dimensional Reference pattern

6.2.2 Distributed Failure – 10%:

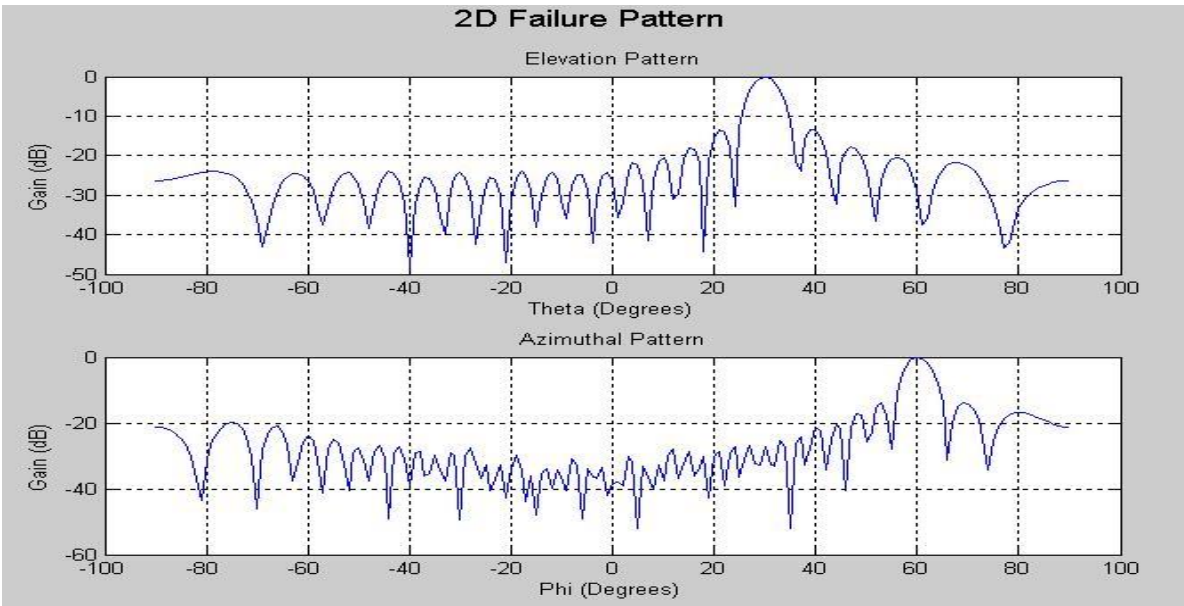


(a)

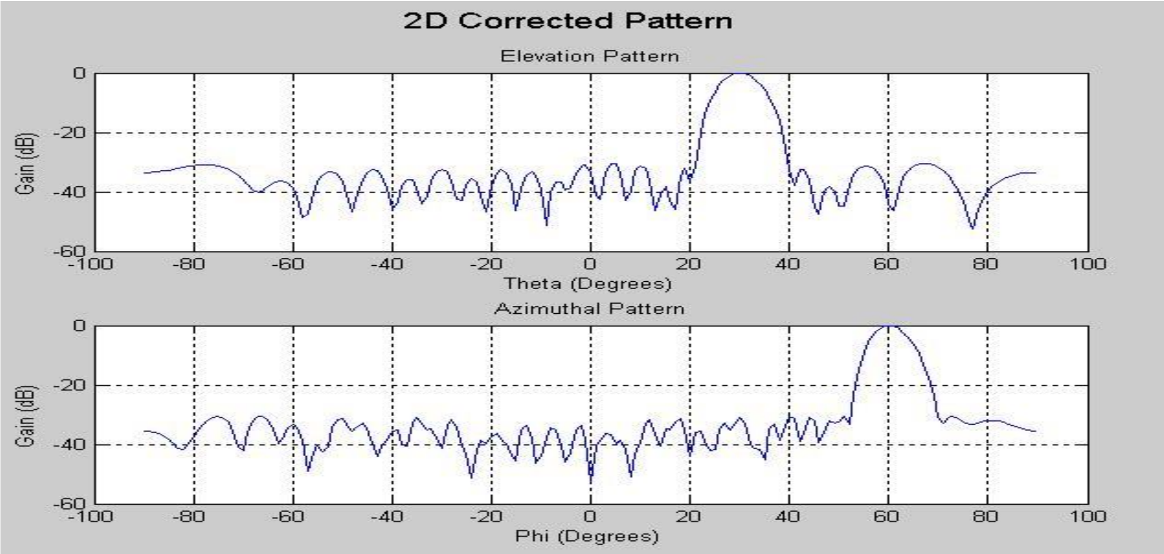




(b) (c)



(d)



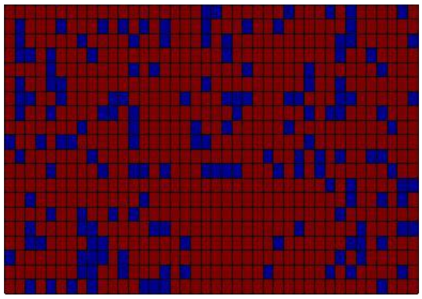
(e)

Figure 6.9: (a) Rectangular antenna array with 10% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

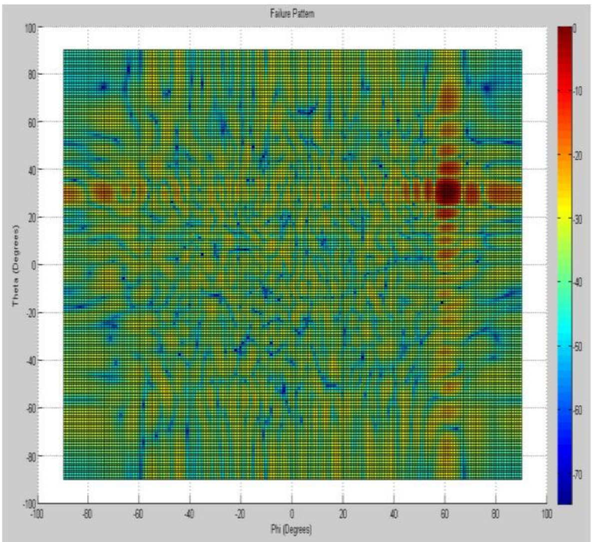
Results for 10% distributed failure in the case of rectangular antenna array are presented. Number of antenna elements failed was 86 and were found to be distributed over the entire antenna array [figure 6.9 (a)]. In the top view of failure pattern [figure 6.9 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -20dB. In the top view of the corrected pattern [figure 6.9 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -30dB to -45dB.

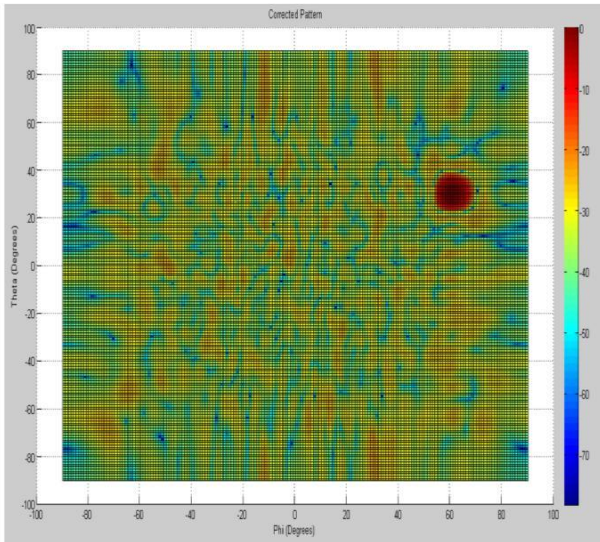
The two-dimensional failure pattern [figure 6.9 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -13.4785dB and -13.5444dB respectively in elevation plane and -13.7632dB and -13.7526dB respectively in azimuthal plane. The mean and of SLLs were found to be -28.6514dB and 7.4337dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -32.0833dB and -32.4657dB respectively in elevation plane and -30.6104dB and -30.6393dB respectively in azimuthal plane, thus showing considerable descent [figure 6.9 (e)]. The mean and of SLLs also showed values close to reference pattern, -36.9321dB and 4.7832dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix B* shows the computed results.

6.2.3 Distributed Failure – 20%:

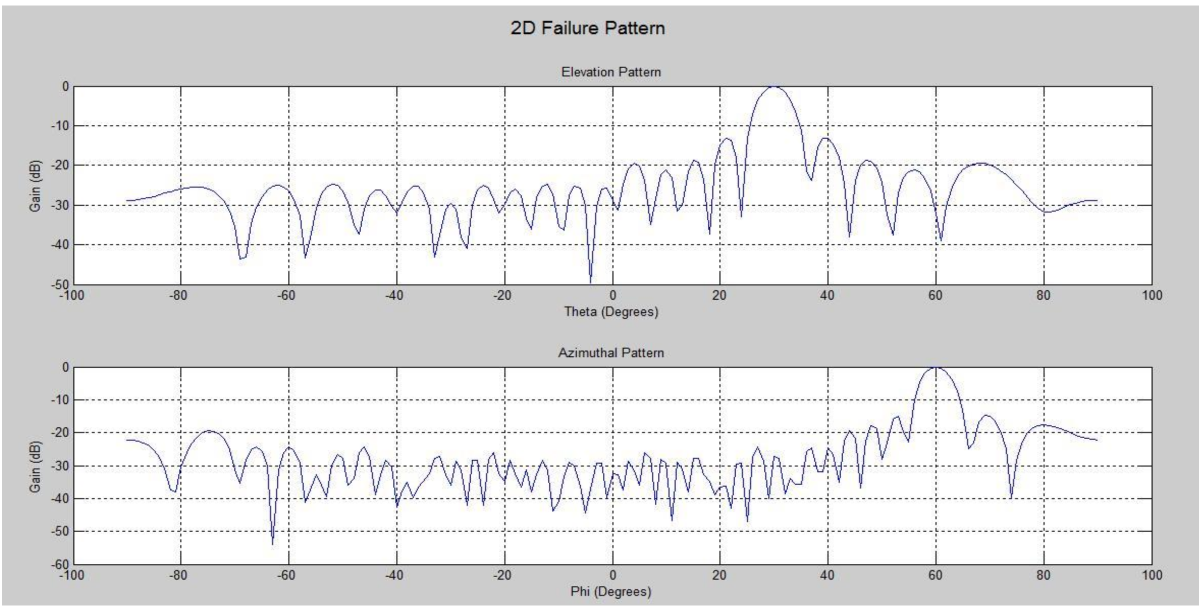


(a)

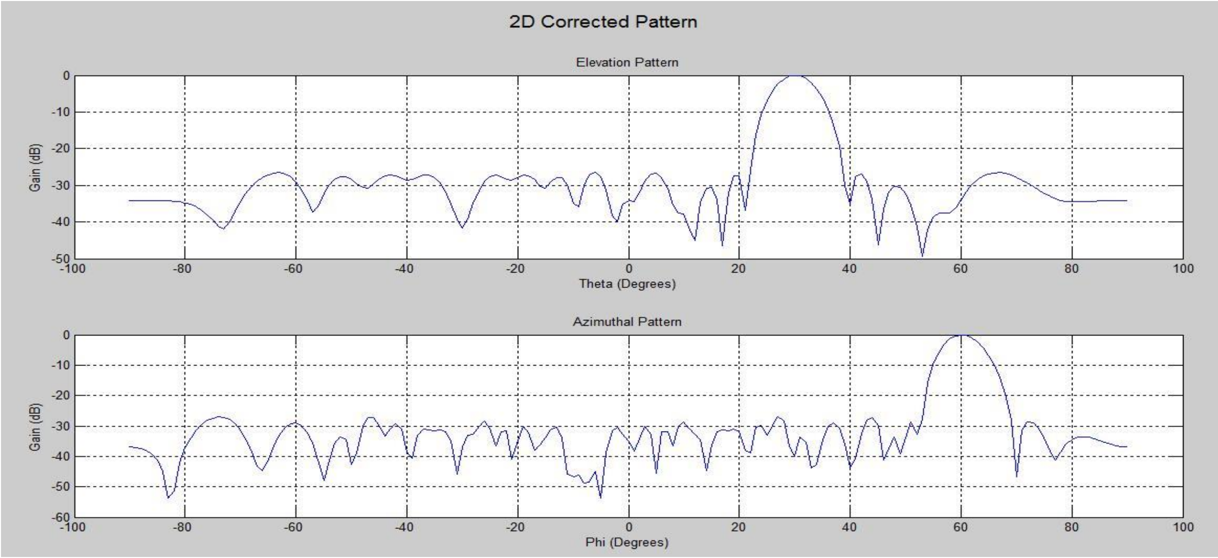




(b) (c)



(d)



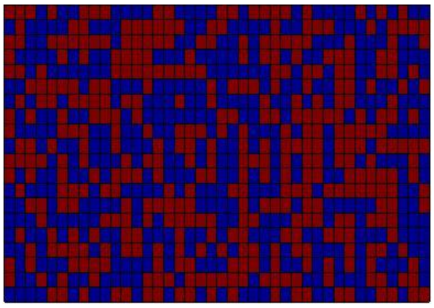
(e)

Figure 6.10: (a) Rectangular antenna array with 20% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

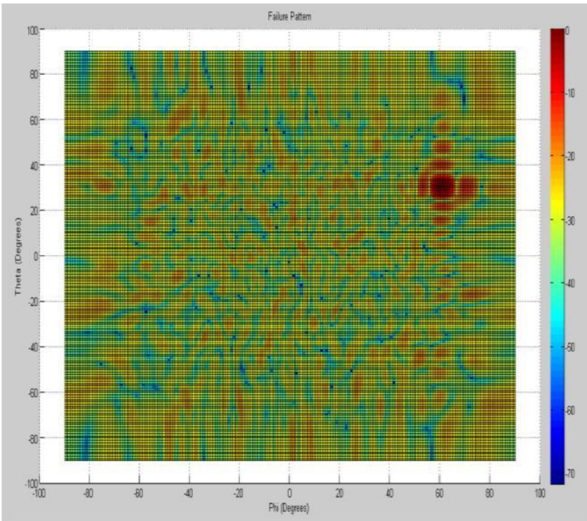
Results for 20% distributed failure in the case of rectangular antenna array are presented. Number of antenna elements failed was 172 and were found to be distributed over the entire antenna array [figure 6.10 (a)]. In the top view of failure pattern [figure 6.10 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -20dB. In the top view of the corrected pattern [figure 6.10 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -25dB to -40dB.

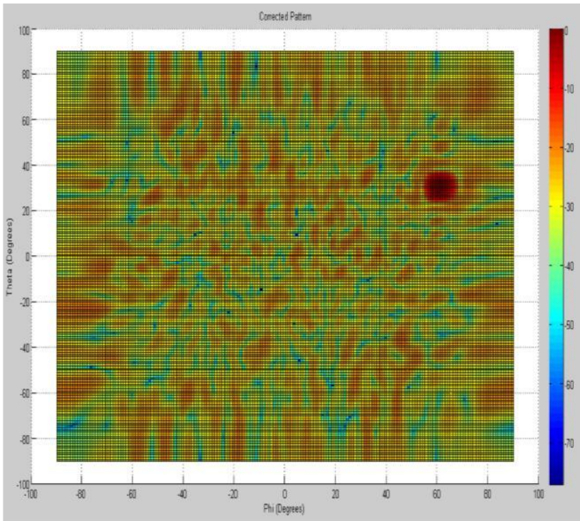
The two-dimensional failure pattern [figure 6.10 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -13.1002dB and -13.1537dB respectively in the elevation plane and -14.8583dB and -14.8397dB respectively in the azimuthal plane. The mean and of SLLs were found to be -28.5404dB and 6.8559dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -27.3058dB and -26.8169dB respectively in the elevation plane and -28.7693dB and -28.8197dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.10 (e)]. The mean and of SLLs also showed values close to reference pattern, -33.7851dB and 5.4299dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix B* shows the computed results.

6.2.4 Distributed Failure – 50%:

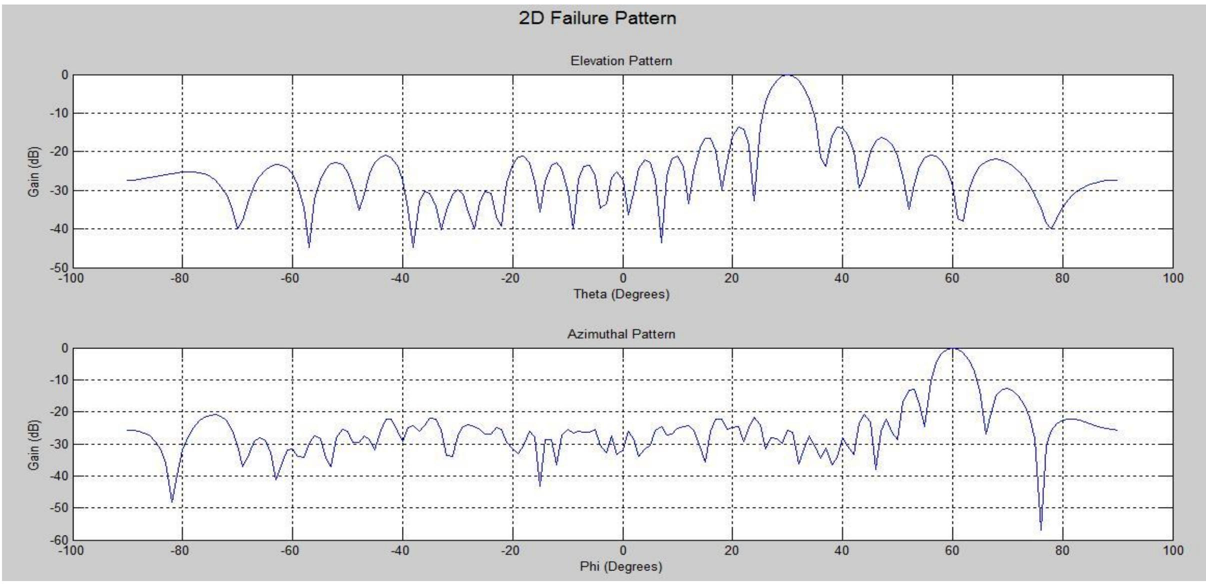


(a)

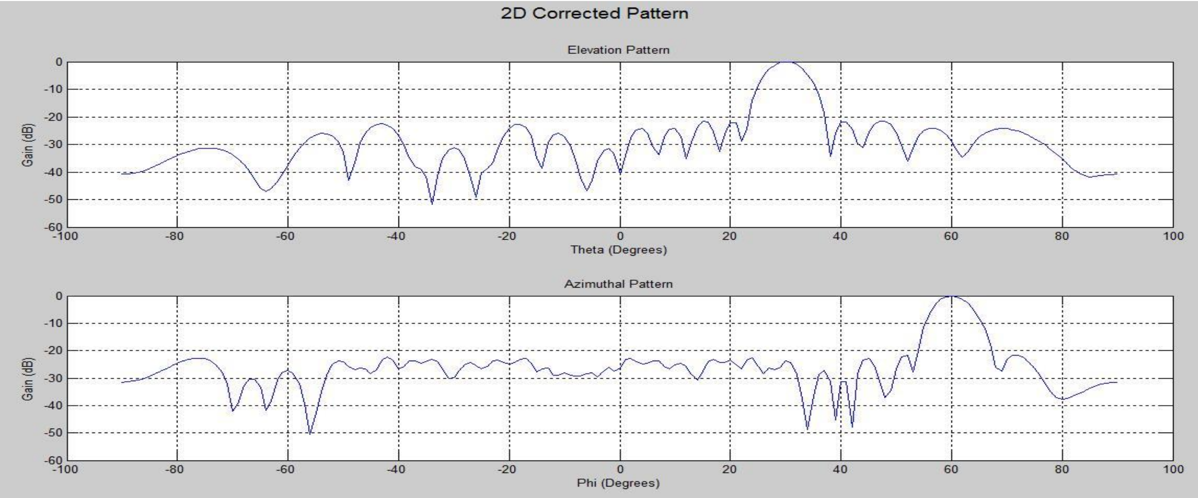




(b) (c)



(d)



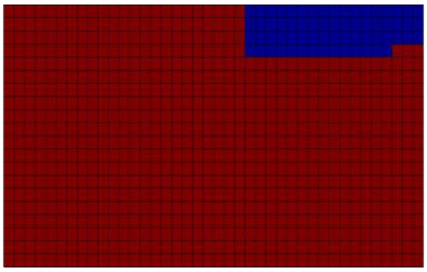
(e)

Figure 6.11: (a) Rectangular antenna array with 50% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

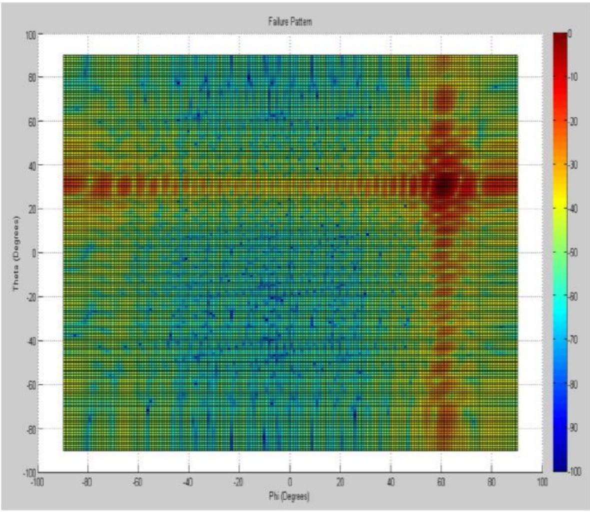
Results for 50% distributed failure in the case of rectangular antenna array are presented. Number of antenna elements failed was 431 and were found to be distributed over the entire antenna array [figure 6.11 (a)]. In the top view of failure pattern [figure 6.11 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -18dB. In the top view of the corrected pattern [figure 6.11 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -20dB to -35dB.

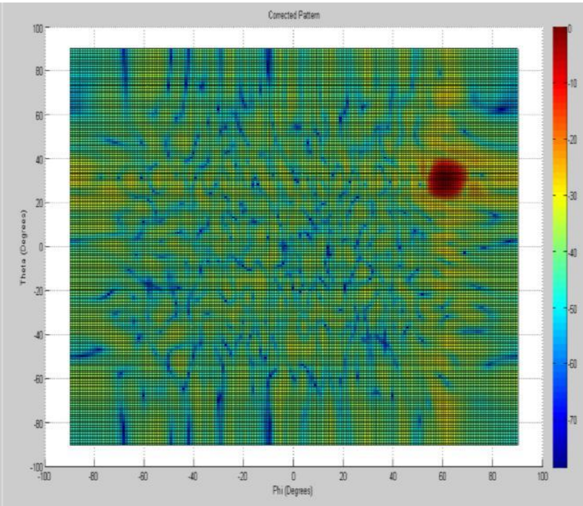
The two-dimensional failure pattern [figure 6.11 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -13.7169dB and -13.6976dB respectively in the elevation plane and -12.9355dB and -12.6498dB respectively in the azimuthal plane. The mean and of SLLs were found to be -27.4871dB and 6.0804dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -22.0798dB and -21.9052dB respectively in the elevation plane and -21.8118dB and -21.6005dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.11 (e)]. The mean and of SLLs also showed values close to reference pattern, -30.2272dB and 6.5037dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and even though not close to the reference pattern, was seen to be much better than failure pattern. *Appendix B* shows the computed results.

6.2.5 Concentrated Failure – 10%:

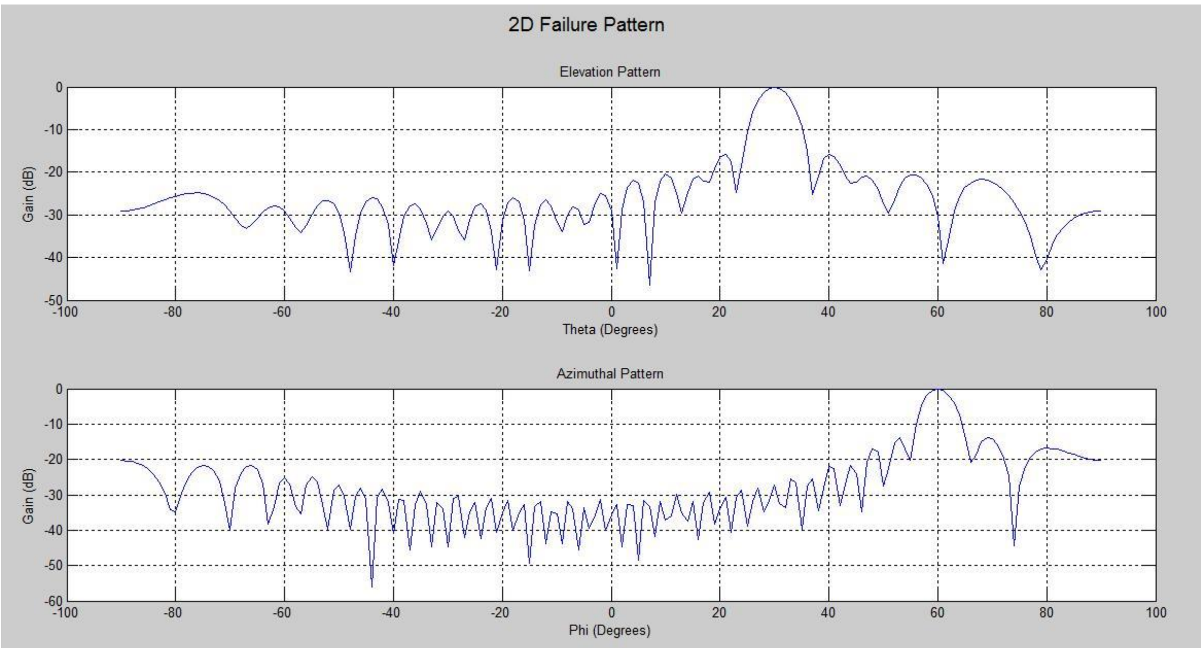


(a)

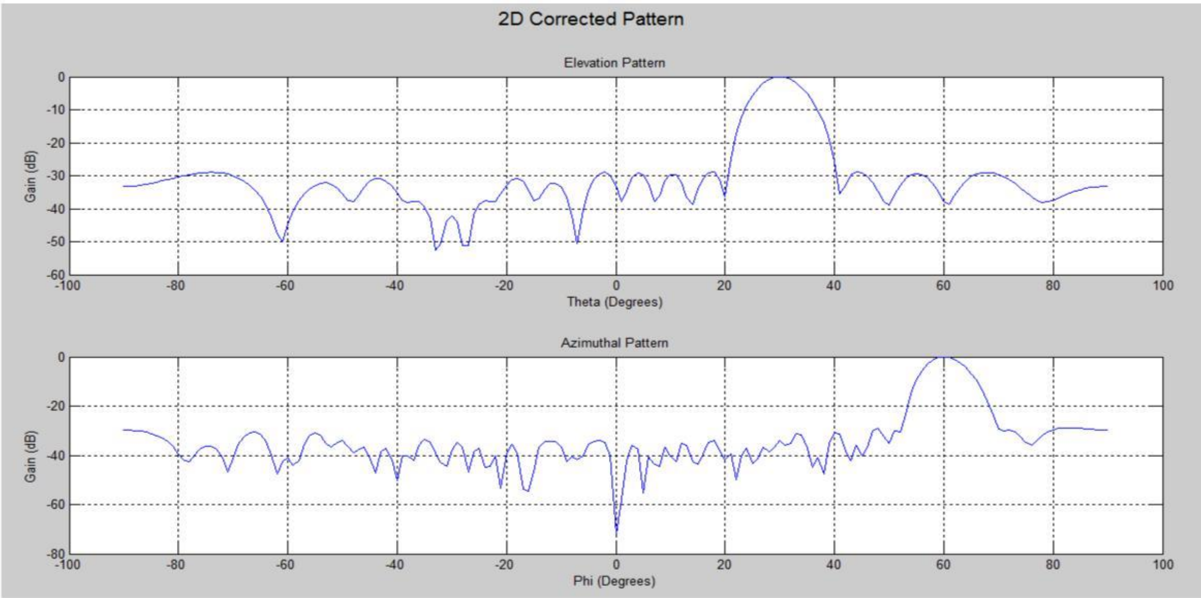




(b) (c)



(d)



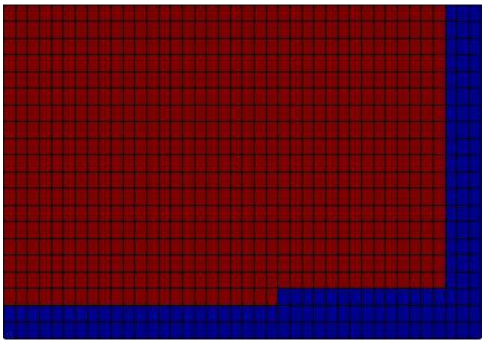
(e)

Figure 6.12: (a) Rectangular antenna array with 10% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

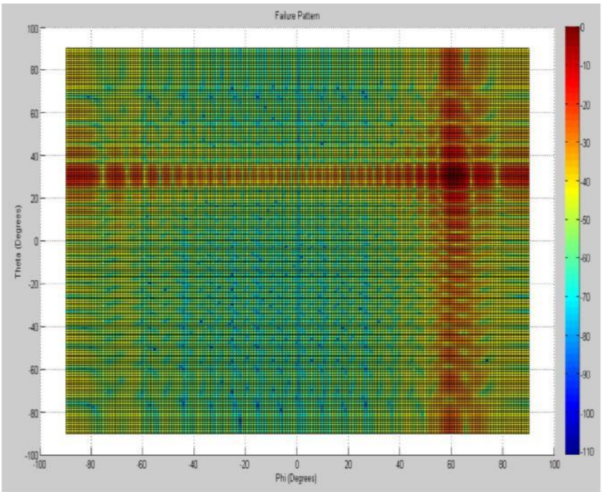
Results for 10% concentrated failure in the case of rectangular antenna array are presented. Number of antenna elements failed was 86 and were found to be concentrated over the top-right region of antenna array [figure 6.12 (a)]. In the top view of failure pattern [figure 6.12 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -25dB. In the top view of the corrected pattern [figure 6.12 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -30dB to -45dB.

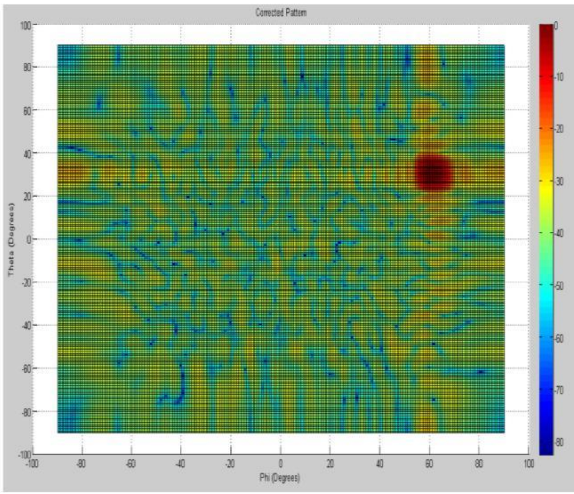
The two-dimensional failure pattern [figure 6.12 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -15.7534dB and -15.7337dB respectively in the elevation plane and -13.8587dB and -13.8486dB respectively in the azimuthal plane. The mean and of SLLs were found to be -29.1302dB and 7.0872dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -28.9291dB and -28.8515dB respectively in the elevation plane and -29.9851dB and -29.5813dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.12 (e)]. The mean and of SLLs also showed values close to reference pattern, -36.298dB and 6.0816dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix B* shows the computed results.

6.2.6 Concentrated Failure – 20%:

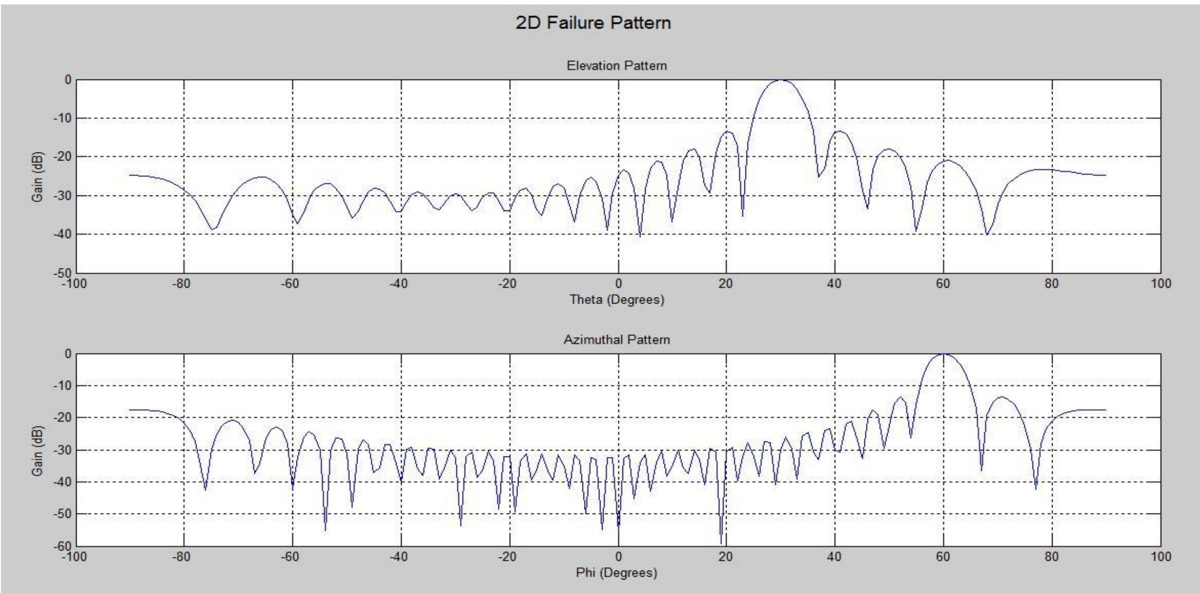


(a)

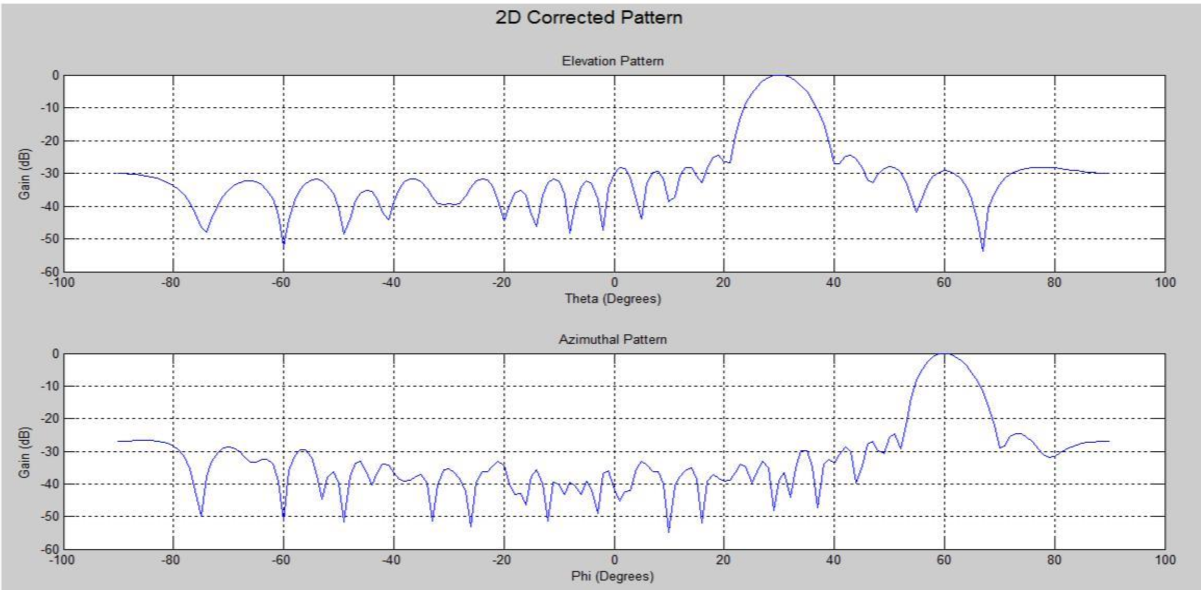




(b) (c)



(d)



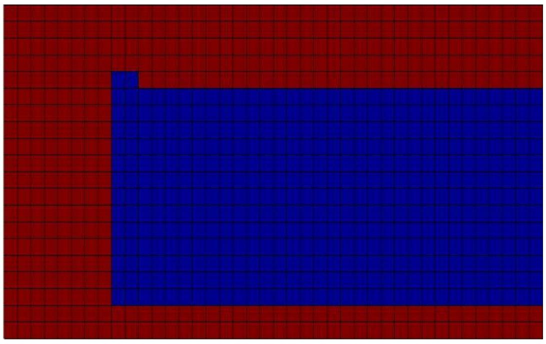
(e)

Figure 6.13: (a) Rectangular antenna array with 20% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

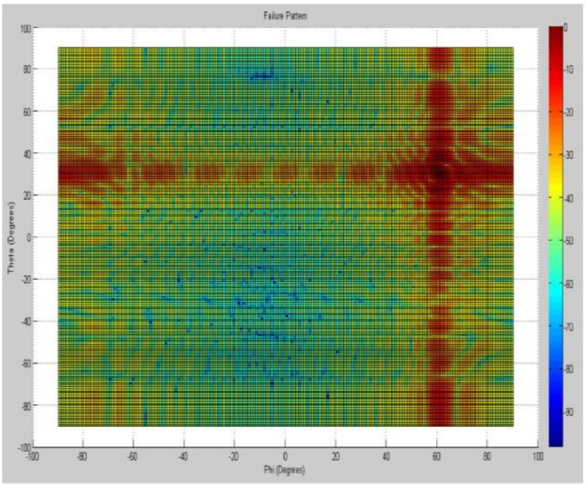
Results for 20% concentrated failure in the case of rectangular antenna array are presented. Number of antenna elements failed was 172 and were found to be concentrated over the right and bottom region of antenna array [figure 6.13 (a)]. In the top view of failure pattern [figure 6.13 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -20dB. In the top view of the corrected pattern [figure 6.13 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -20dB to -40dB.

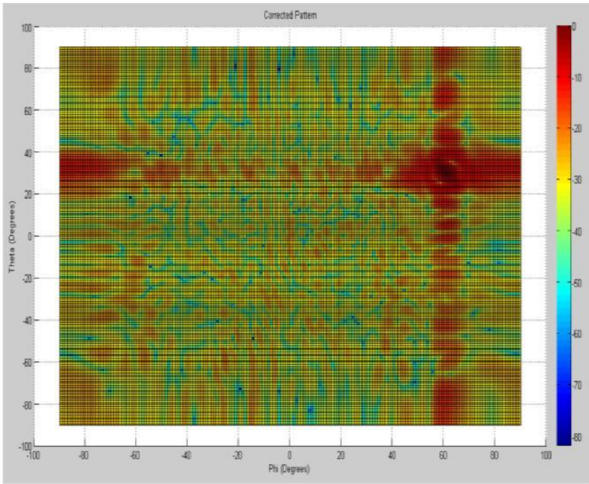
The two-dimensional failure pattern [figure 6.13 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -13.3672dB and -13.3184dB respectively in the elevation plane and -13.518dB and -13.5787dB respectively in the azimuthal plane. The mean and of SLLs were found to be -28.6493dB and 7.6898dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -24.4363dB and -24.4515dB respectively in the elevation plane and -24.6211dB and-24.4851dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.13 (e)]. The mean and of SLLs also showed values close to reference pattern, -35.0615dB and 6.1354dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix B* shows the computed results.

6.2.7 Concentrated Failure – 50%:

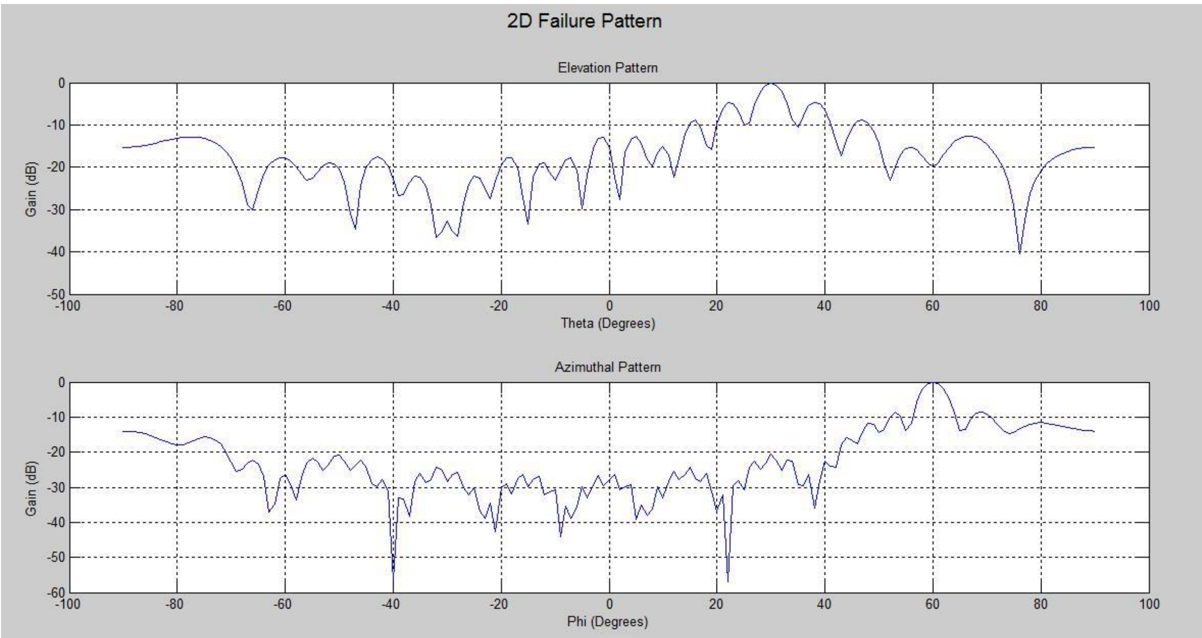


(a)

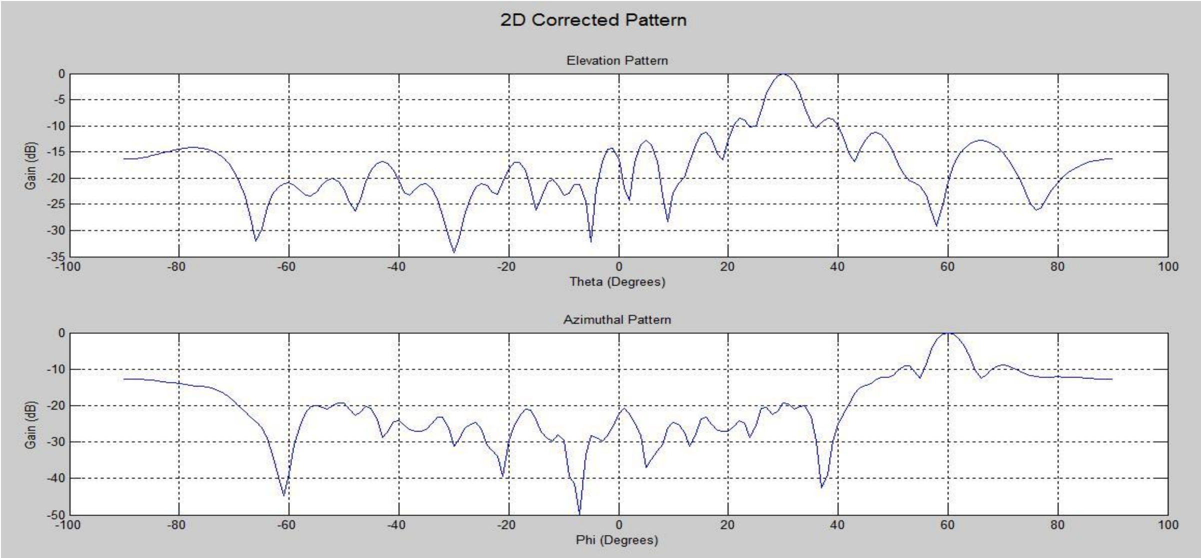




(b) (c)



(d)



(e)

Figure 6.14: (a) Rectangular antenna array with 50% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

Results for 50% concentrated failure in the case of rectangular antenna array are presented. Number of antenna elements failed was 431 and were found to be concentrated over the center region of antenna array [figure 6.14 (a)]. In the top view of failure pattern [figure 6.14 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -2dB to -15dB. In the top view of the corrected pattern [figure 6.14 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -25dB.

The two-dimensional failure pattern [figure 6.14 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -4.762dB and -4.6659dB respectively in the elevation plane and -8.64dB and -8.6435dB respectively in the azimuthal plane. The mean and of SLLs were found to be -21.3975dB and 8.3293dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -8.5447dB and -8.5646dB respectively in the elevation plane and -9.0279dB and -8.8479dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.14 (e)]. The mean and of SLLs also showed values close to reference pattern, -20.6674dB and 6.9915dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was better than the failure pattern. *Appendix B* shows the computed results.

6.3 HEXAGONAL ANTENNA ARRAY:

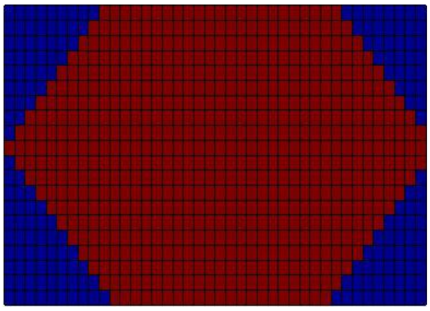
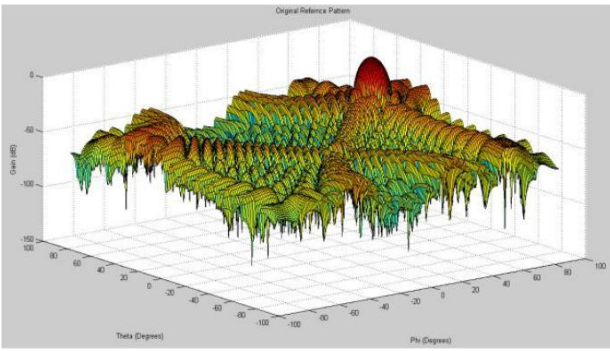
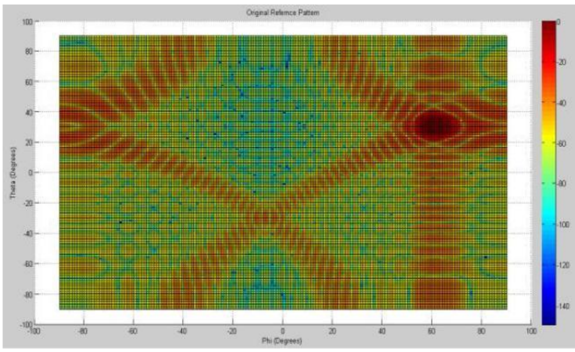


Figure 6.15: Hexagonal Antenna Array

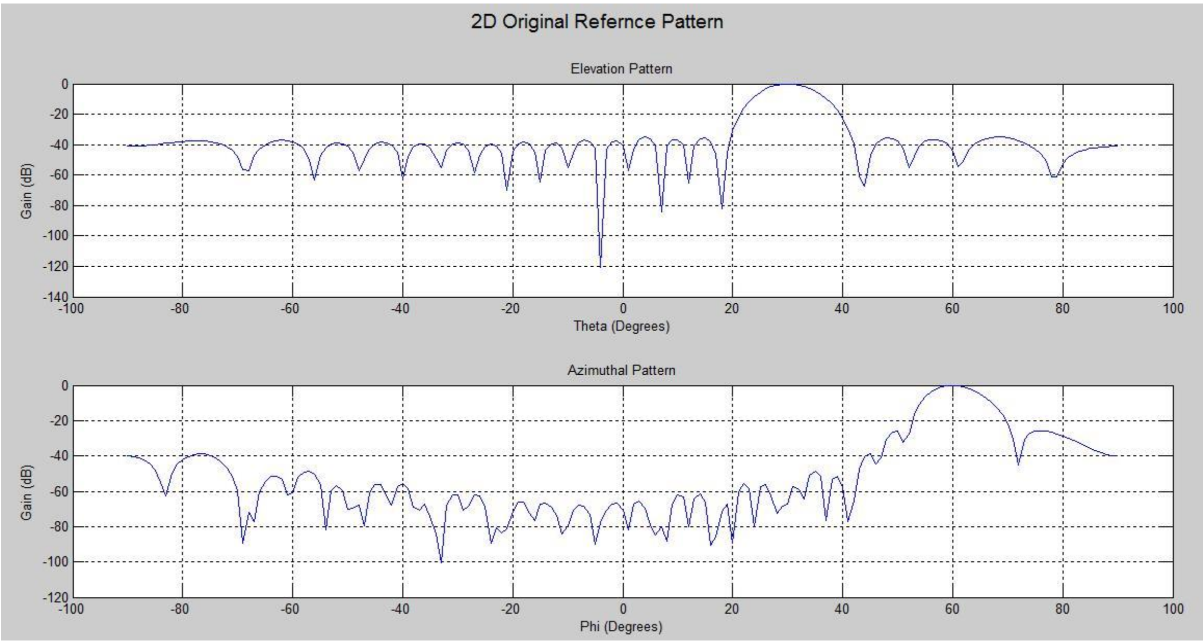
6.2.1 Taylor Reference:



(a)



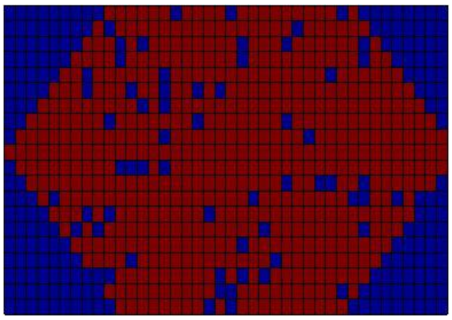
(b)



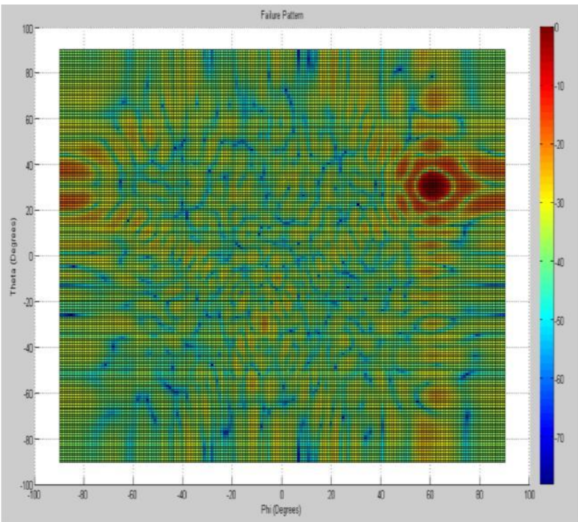
(c)

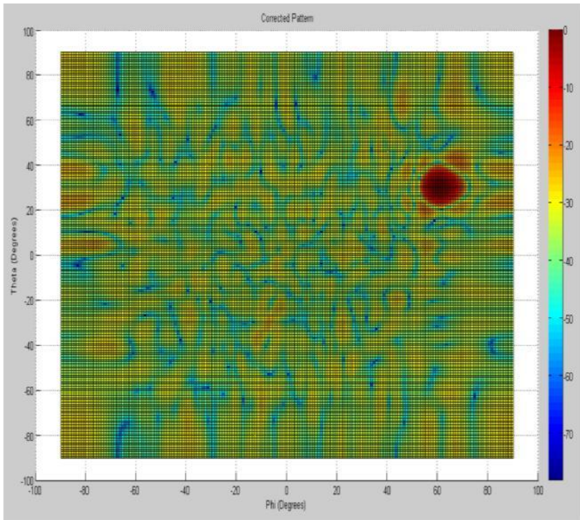
Figure 6.16: (a) Three-Dimensional Reference Pattern, (b) XY view (top view), (c) Two-Dimensional Reference pattern

6.3.2 Distributed Failure – 10%:

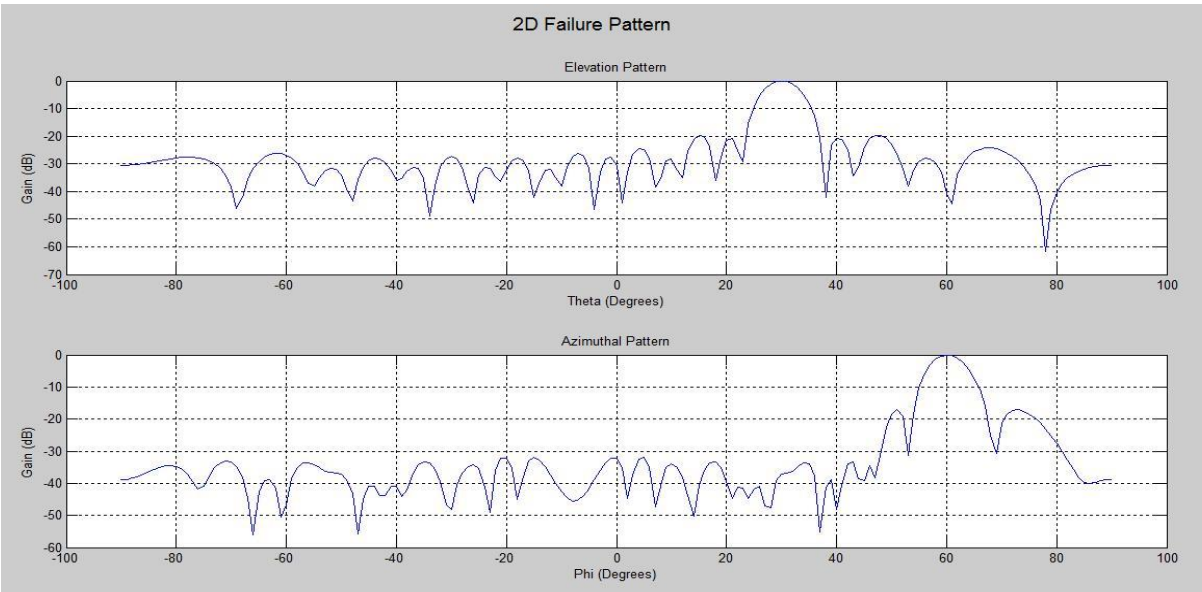


(a)

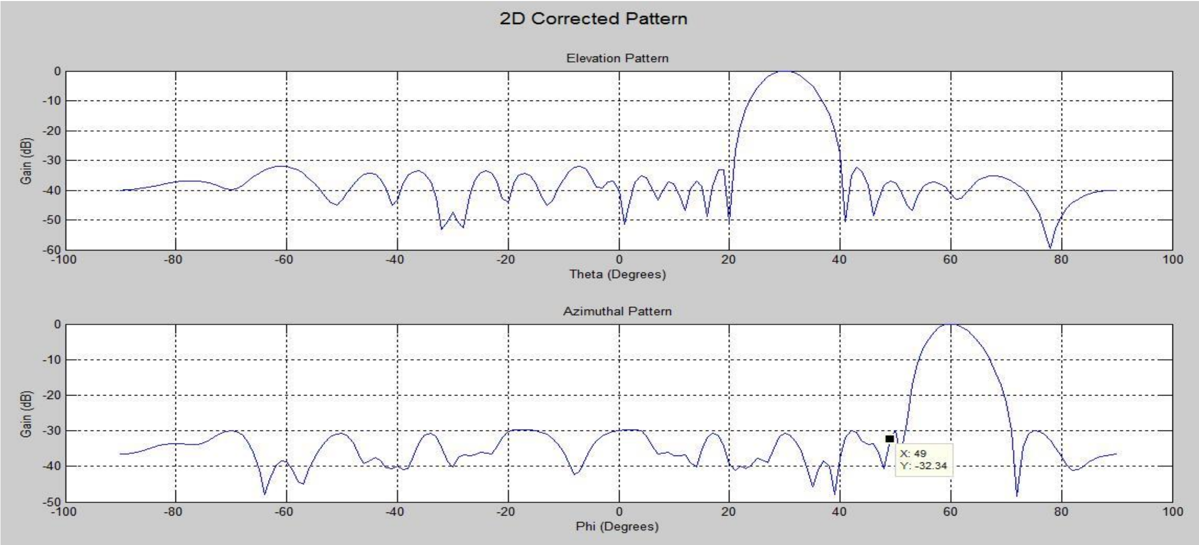




(b) (c)



(d)



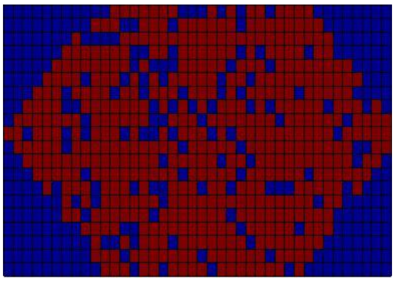
(e)

Figure 6.17: (a) Hexagonal antenna array with 10% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

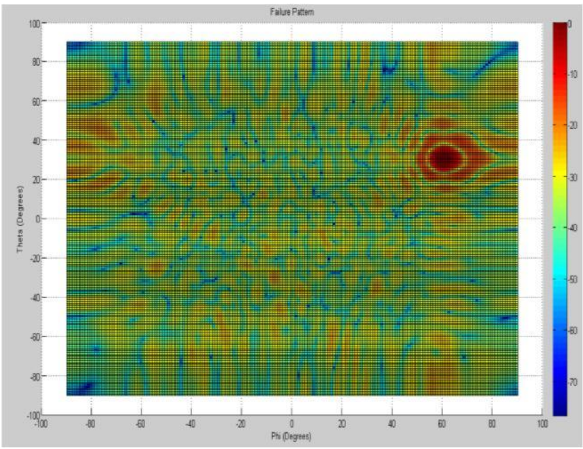
Results for 10% distributed failure in the case of hexagonal antenna array are presented. Number of antenna elements failed was 64 and were found to be distributed over the entire antenna array [figure 6.17 (a)]. In the top view of failure pattern [figure 6.17 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -25dB. In the top view of the corrected pattern [figure 6.17 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -30dB to -45dB.

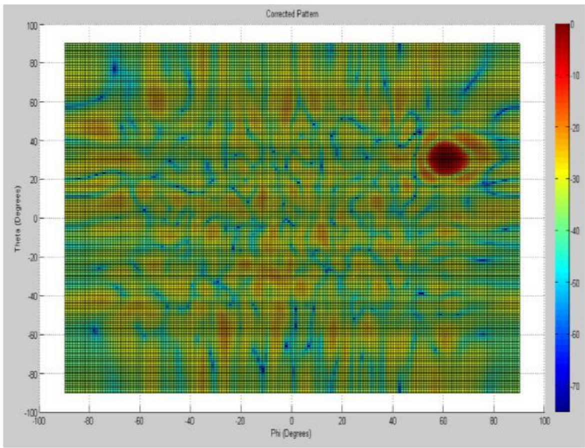
The two-dimensional failure pattern [figure 6.17 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -20.7152dB and -20.6448dB respectively in the elevation plane and -17.1146dB and -17.1352dB respectively in the azimuthal plane. The mean and of SLLs were found to be -34.3778dB and 7.1952dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -33.123dB and -32.4559dB respectively in the elevation plane, and -29.8814dB and -29.886dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.17 (e)]. The mean and of SLLs also showed values close to reference pattern, -37.4881dB and 4.9967dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix C* shows the computed results.

6.3.3 Distributed Failure – 20%:

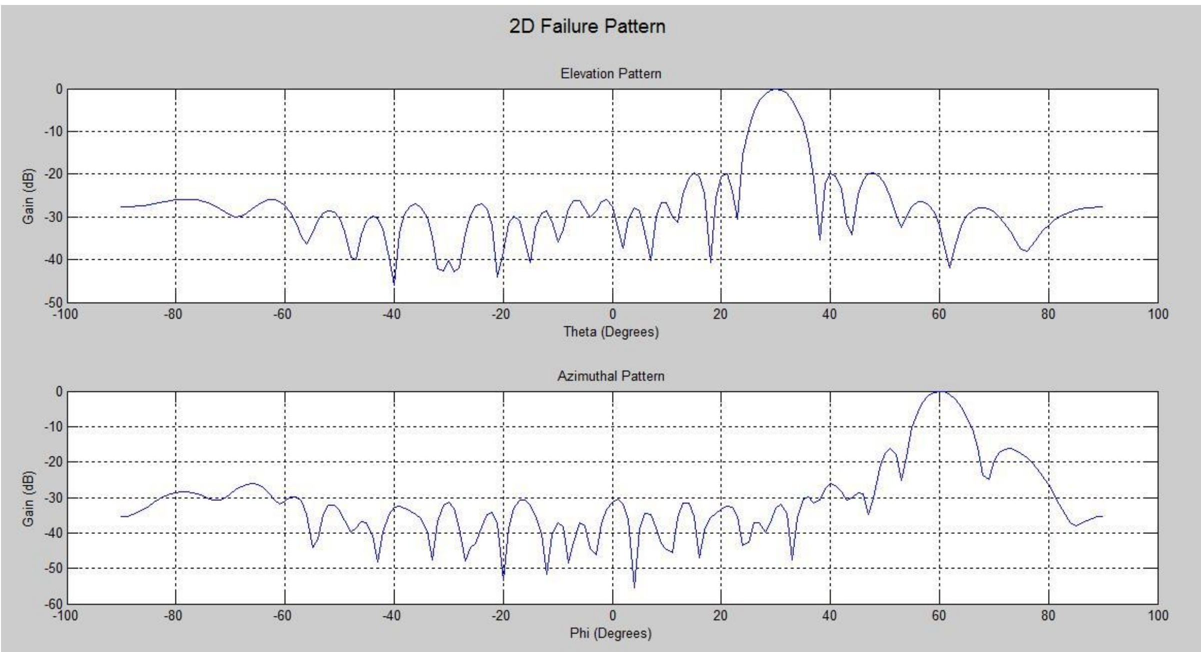


(a)

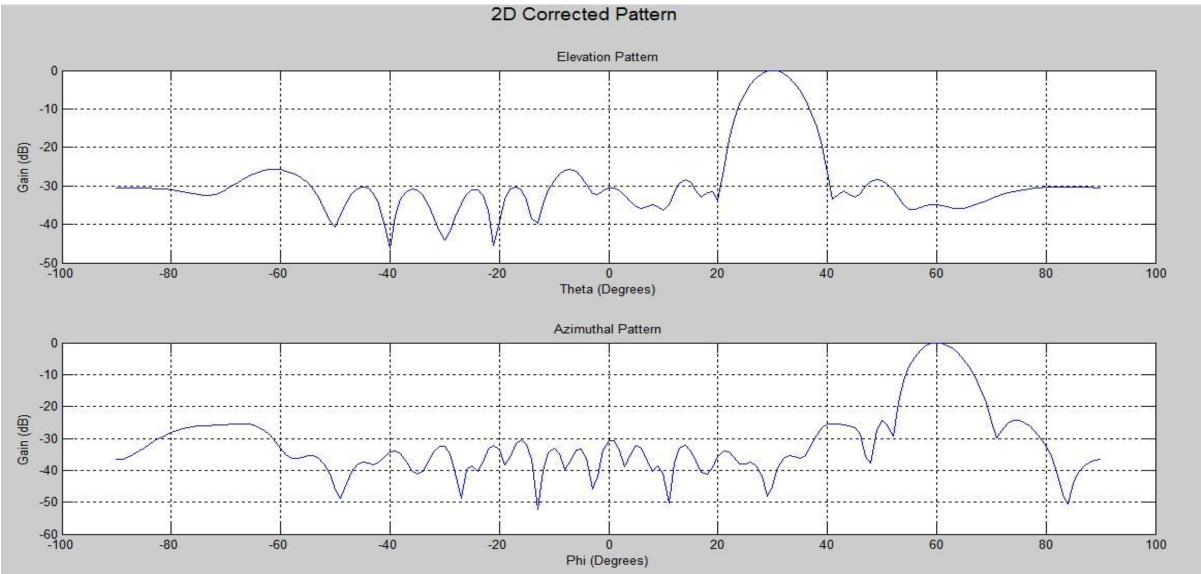




(b) (c)



(d)



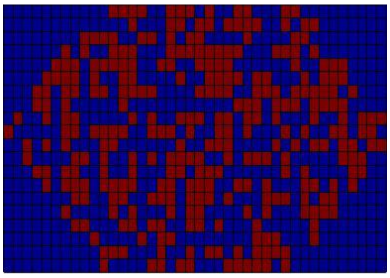
(e)

Figure 6.18: (a) Hexagonal antenna array with 20% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

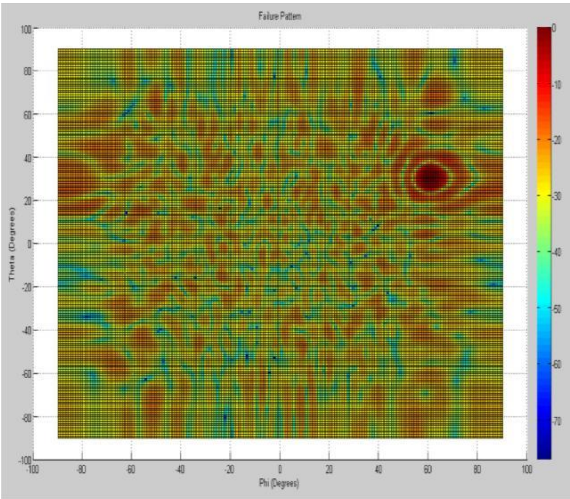
Results for 20% distributed failure in the case of hexagonal antenna array are presented. Number of antenna elements failed was 128 and were found to be distributed over the entire antenna array [figure 6.18 (a)]. In the top view of failure pattern [figure 6.18 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -25dB. In the top view of the corrected pattern [figure 6.18 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -28dB to -40dB.

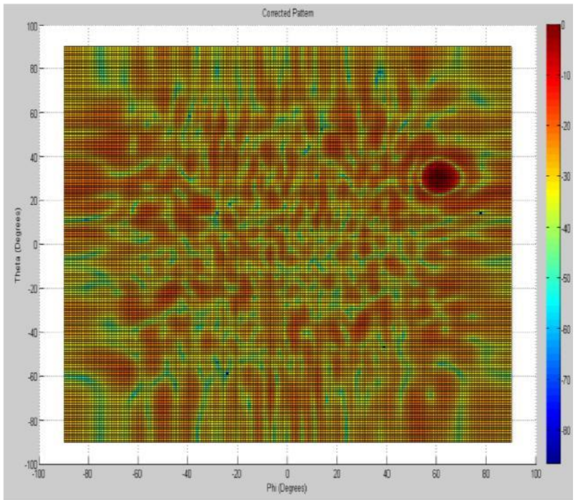
The two-dimensional failure pattern [figure 6.18 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -19.9032dB and -19.9032dB respectively in the elevation plane and -16.2635dB and -16.2925dB respectively in the azimuthal plane. The mean and of SLLs were found to be -32.0507dB and 6.4402dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -31.5974dB and -31.3451dB respectively in the elevation plane, and -24.4201dB and -24.396dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.18 (e)]. The mean and of SLLs also showed values close to reference pattern, -33.5476dB and 5.2124dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix C* shows the computed results.

6.3.4 Distributed Failure – 50%:

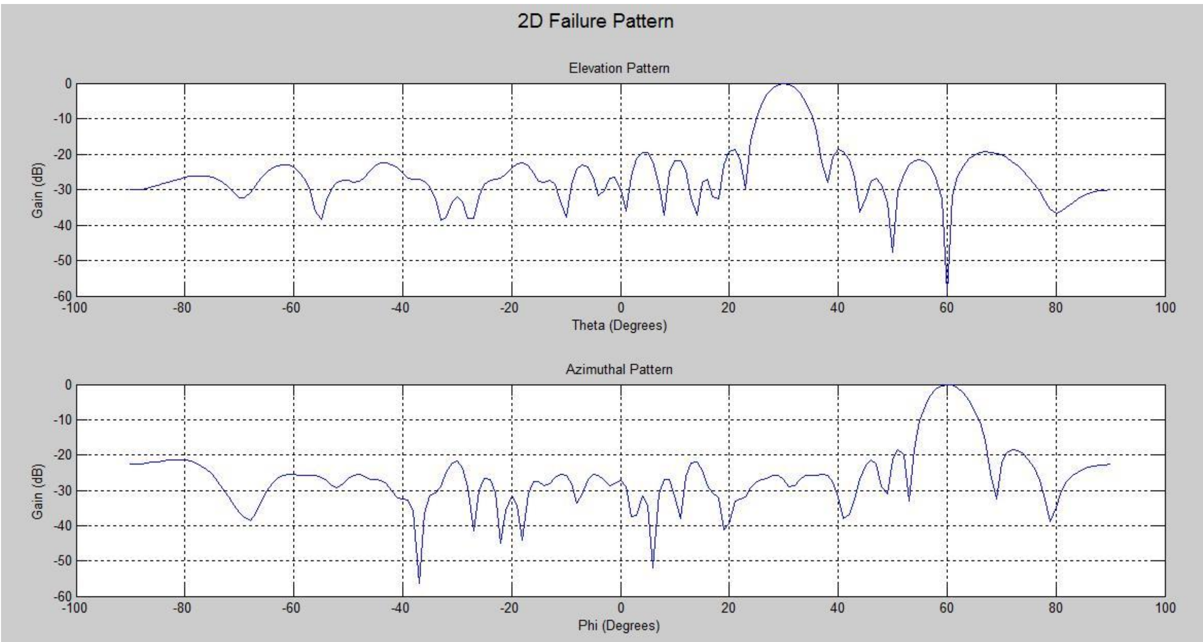


(a)

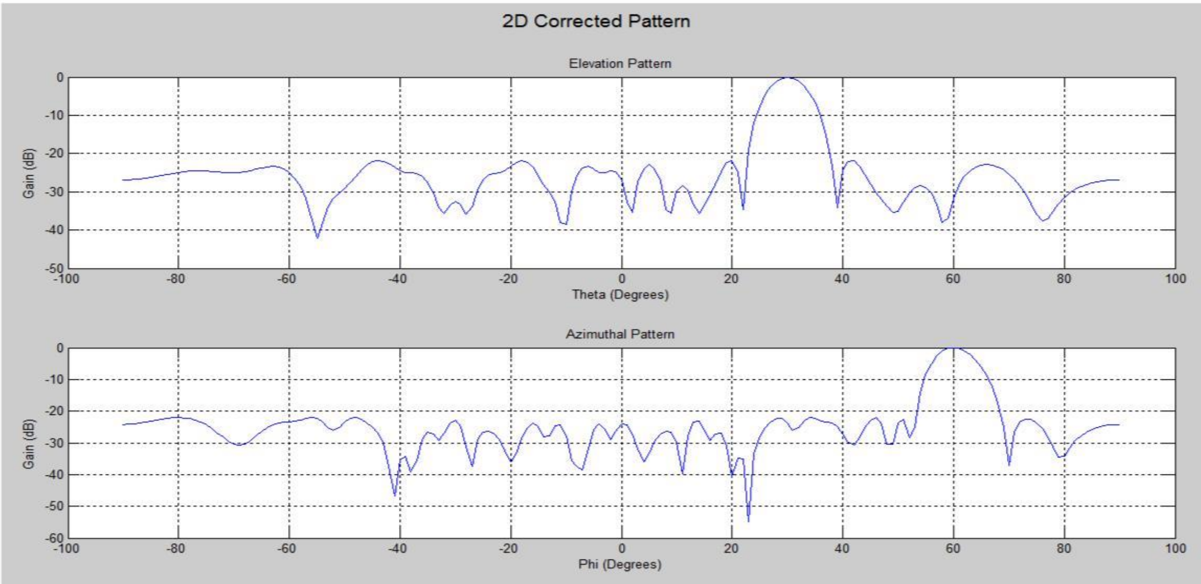




(b) (c)



(d)



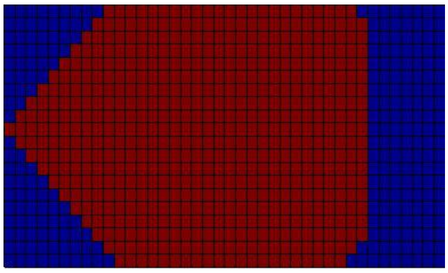
(e)

Figure 6.19: (a) Hexagonal antenna array with 50% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

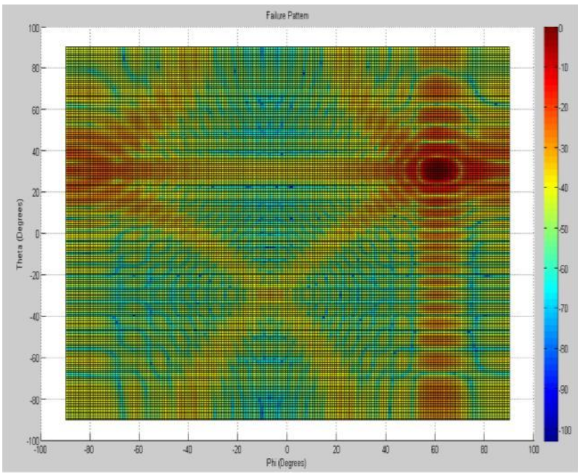
Results for 50% distributed failure in the case of hexagonal antenna array are presented. Number of antenna elements failed was 321 and were found to be distributed over the entire antenna array [figure 6.19 (a)]. In the top view of failure pattern [figure 6.19 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -25dB. In the top view of the corrected pattern [figure 6.19 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -22dB to -35dB.

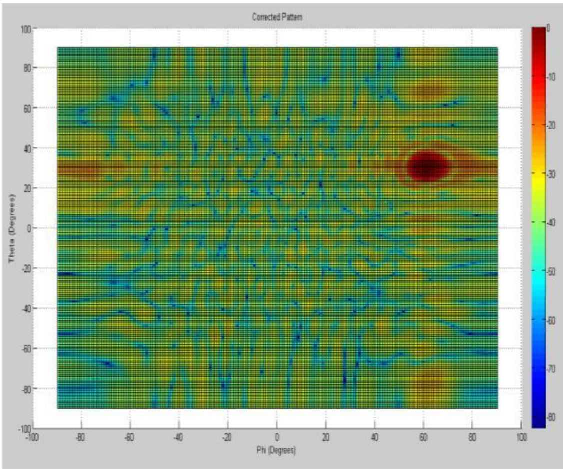
The two-dimensional failure pattern [figure 6.19 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -18.7581dB and -18.7047dB respectively in the elevation plane and -18.5597dB and-18.5079dB respectively in the azimuthal plane. The mean and of SLLs were found to be -28.2615dB and 5.7395dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -21.9294dB and -21.9434dB respectively in the elevation plane and -22.5742dB and -22.4476dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.19 (e)]. The mean and of SLLs also showed values close to reference pattern, -27.6726dB and 4.8541dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was better than failure pattern. *Appendix C* shows the computed results.

6.3.5 Concentrated Failure – 10%:

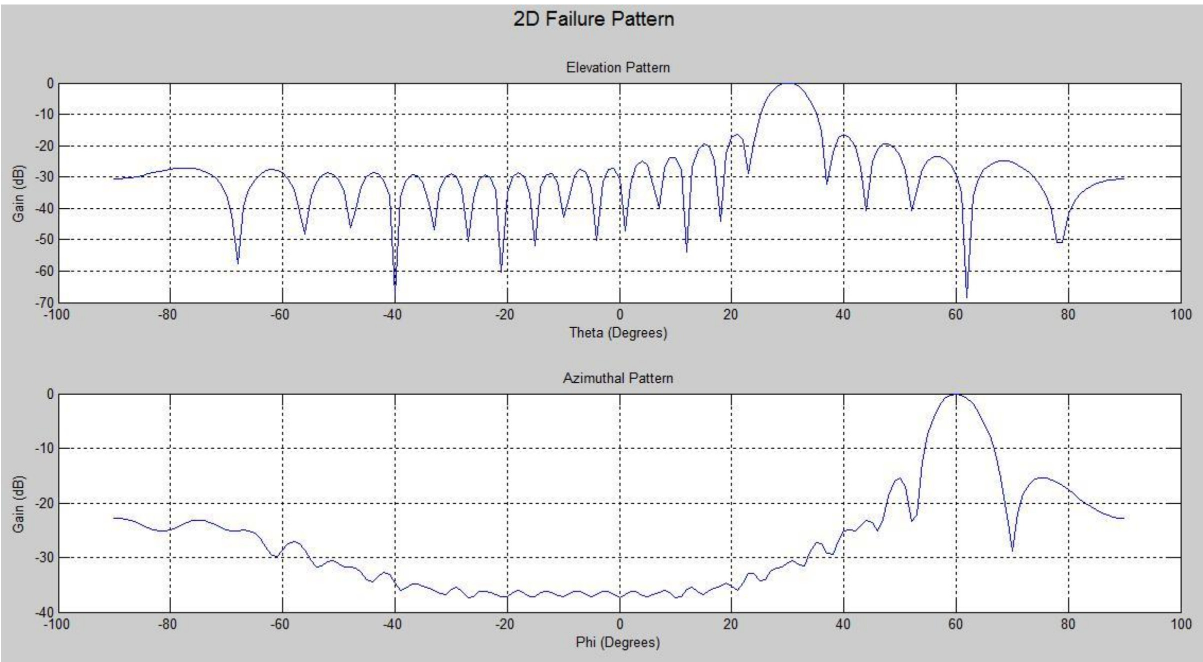


(a)

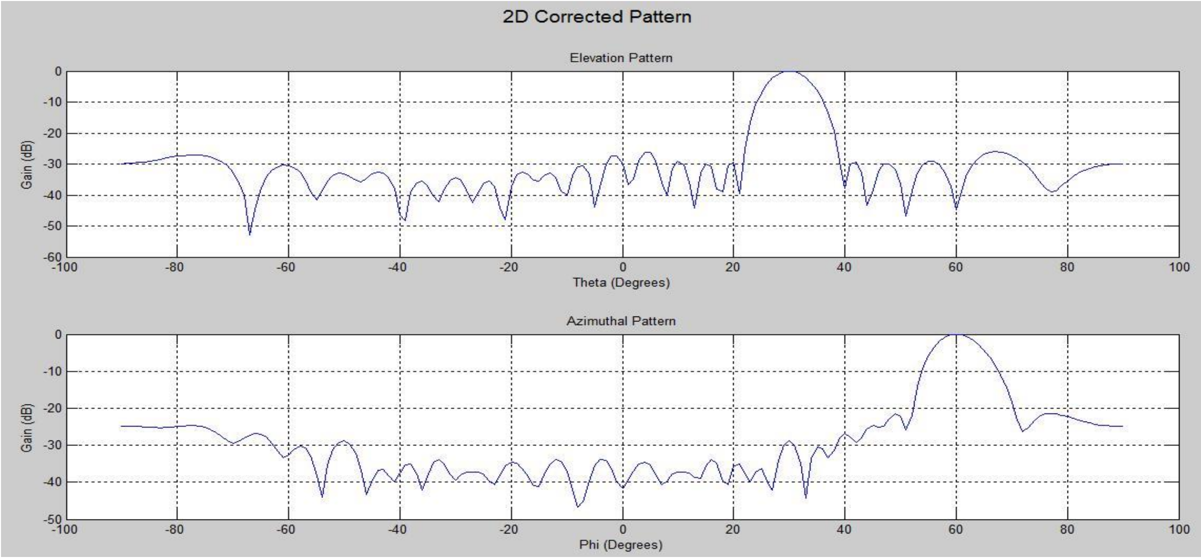




(b) (c)



(d)



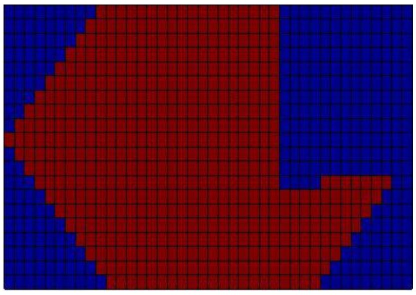
(e)

Figure 6.20: (a) Hexagonal antenna array with 10% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

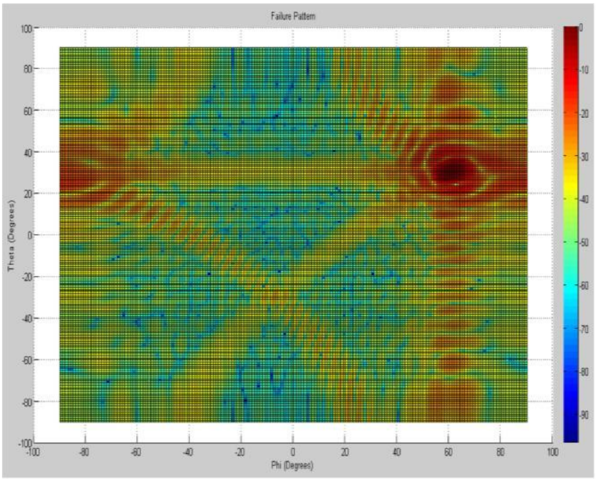
Results for 10% concentrated failure in the case of hexagonal antenna array are presented. Number of antenna elements failed was 64 and were found to be concentrated over the right region of antenna array [figure 6.20 (a)]. In the top view of failure pattern [figure 6.20 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -15dB to -30dB. In the top view of the corrected pattern [figure 6.20 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -28dB to -42dB.

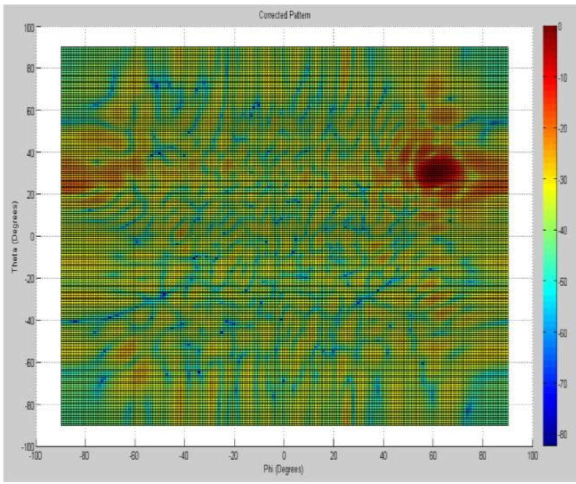
The two-dimensional failure pattern [figure 6.20 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -16.2478dB and -16.2471dB respectively in the elevation plane and -15.3523dB and -15.3543dB respectively in the azimuthal plane. The mean and of SLLs were found to be -30.9386dB and 7.7579dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -29.5503dB and -29.5172dB respectively in the elevation plane and -21.5004dB and -21.4101dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.20 (e)]. The mean and of SLLs also showed values close to reference pattern, -33.2474dB and 5.7687dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix C* shows the computed results.

6.3.6 Concentrated Failure – 20%:

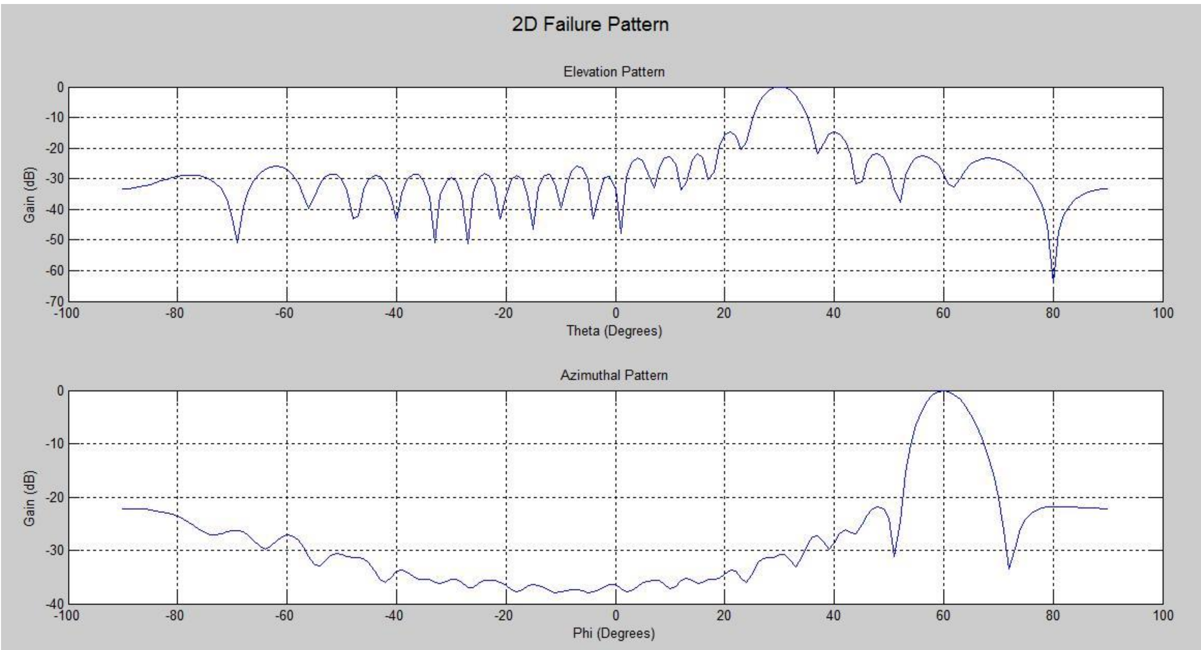


(a)

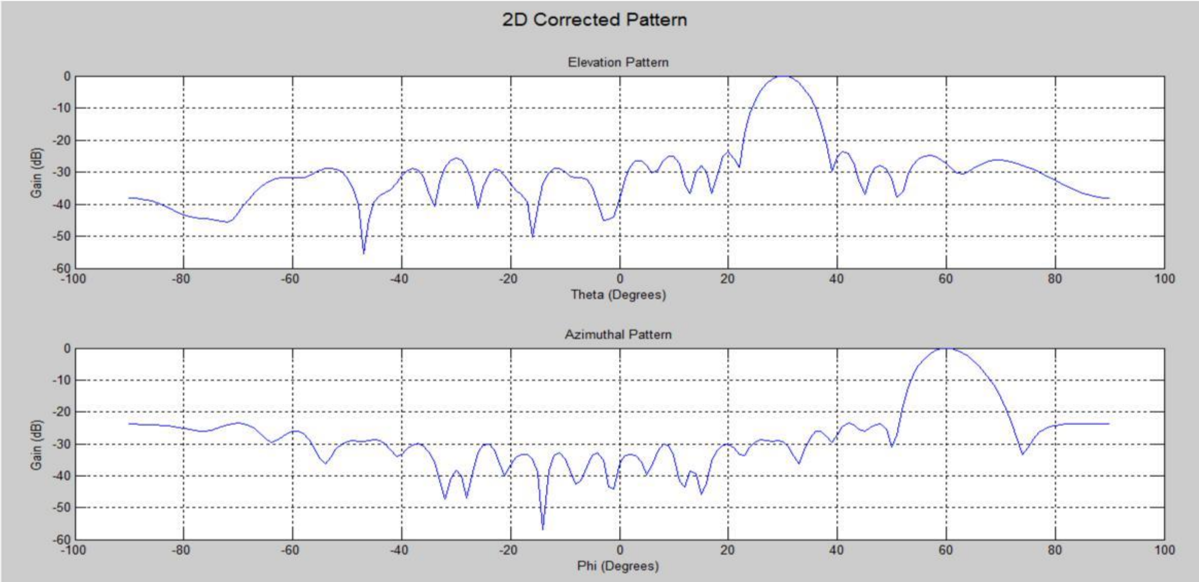




(b) (c)



(d)



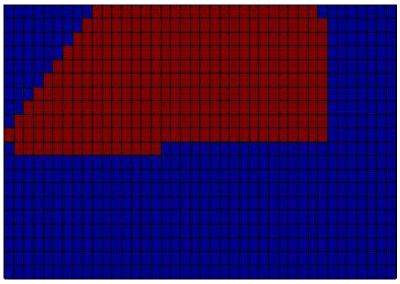
(e)

Figure 6.21: (a) Hexagonal antenna array with 20% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

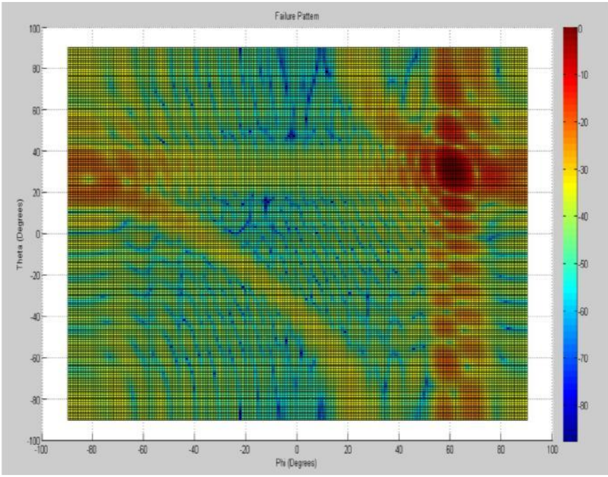
Results for 20% concentrated failure in the case of hexagonal antenna array are presented. Number of antenna elements failed was 128 and were found to be concentrated over the top-right region of antenna array [figure 6.21 (a)]. In the top view of failure pattern [figure 6.21 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -25dB. In the top view of the corrected pattern [figure 6.21 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -25dB to -40dB.

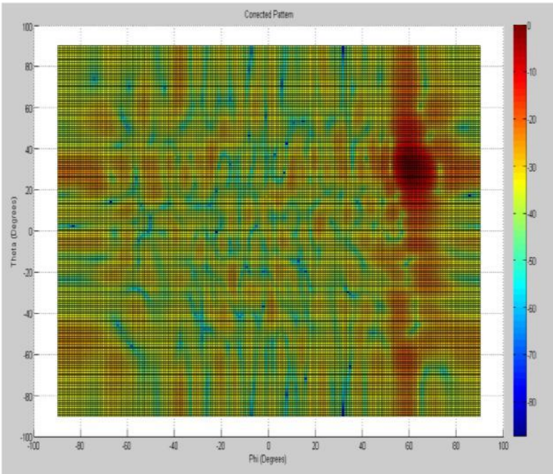
The two-dimensional failure pattern [figure 6.21 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -14.6054dB and -14.609dB respectively in the elevation plane and -21.8206dB and -21.8161dB respectively in the azimuthal plane. The mean and of SLLs were found to be -30.9107dB and 6.4367dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -23.5013dB and -23.5423dB respectively in the elevation plane and -23.8519dB and -23.7102dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.21 (e)]. The mean and of SLLs also showed values close to reference pattern, -32.3075dB and 6.2917dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix C* shows the computed results.

6.3.7 Concentrated Failure – 50%:

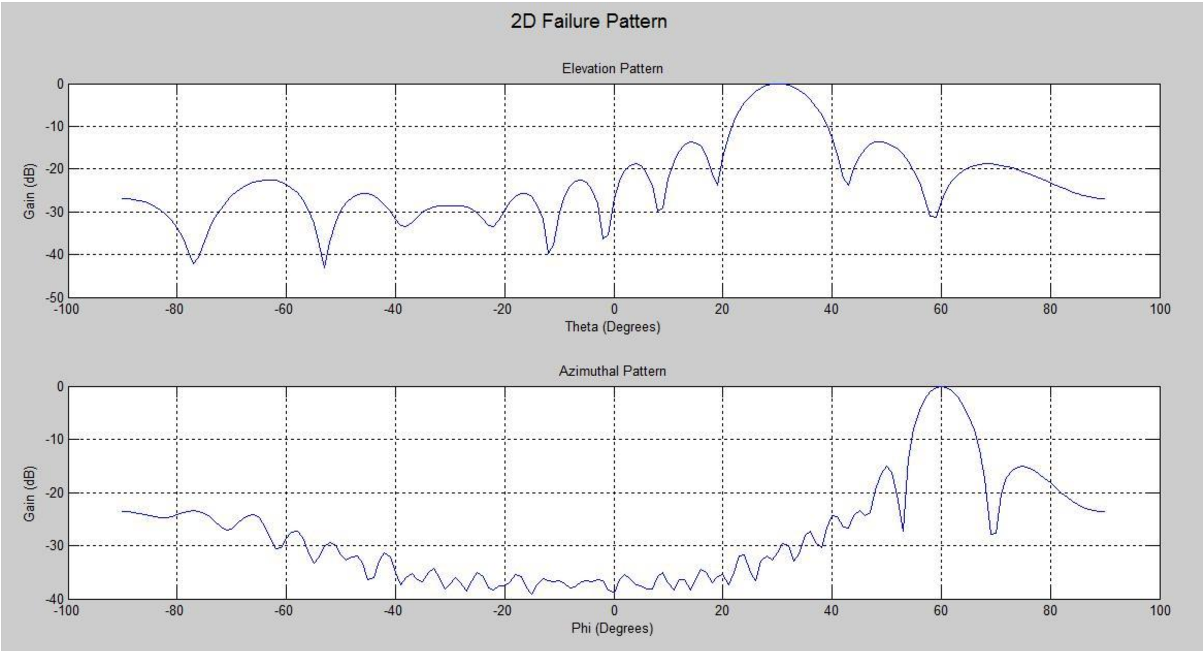


(a)

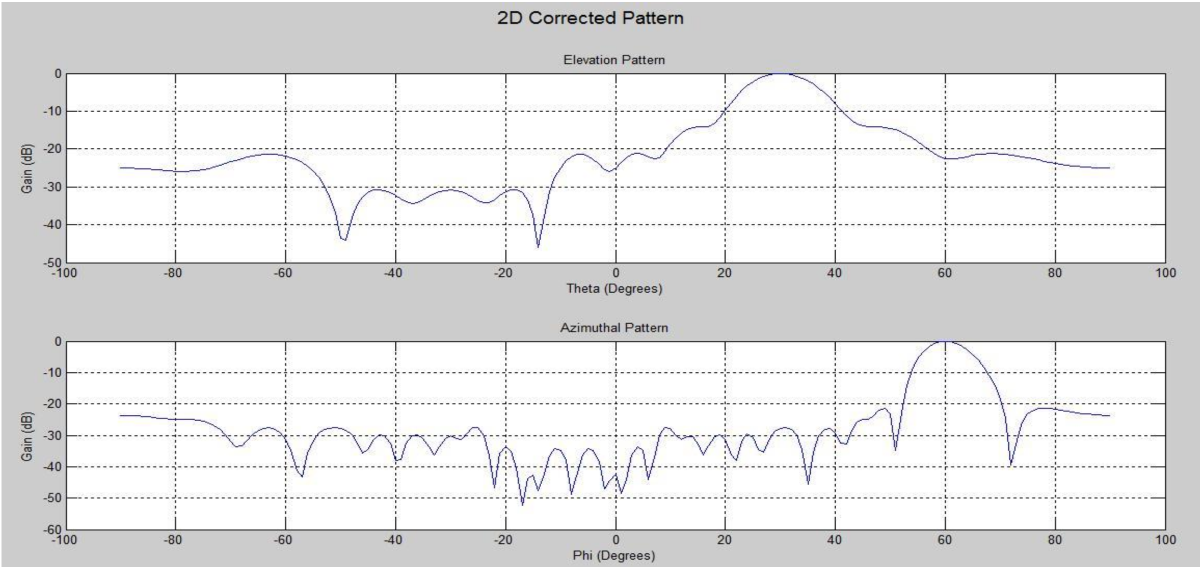




(b) (c)



(d)



(e)

Figure 6.22: (a) Hexagonal antenna array with 50% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

Results for 50% concentrated failure in the case of hexagonal antenna array are presented. Number of antenna elements failed was 321 and were found to be concentrated over the entire bottom-right region of antenna array [figure 6.22 (a)]. In the top view of failure pattern [figure 6.22 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -20dB. In the top view of the corrected pattern [figure 6.22 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -18dB to -35dB.

The two-dimensional failure pattern [figure 6.22 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -13.6891dB and -13.643dB respectively in the elevation plane and -15.1344dB and -15.1327dB respectively in the azimuthal plane. The mean and of SLLs were found to be -28.228dB and 6.7498dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -14.1861 dB and -14.1915dB respectively in the elevation plane and -21.3039dB and -21.2895dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.22 (e)]. The mean and of SLLs also showed values close to reference pattern, -29.4925dB and 6.4484dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was better than failure pattern. *Appendix C* shows the computed results.

6.4 Rhombic Antenna Array:

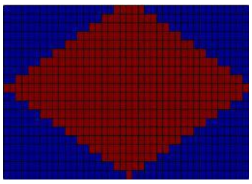
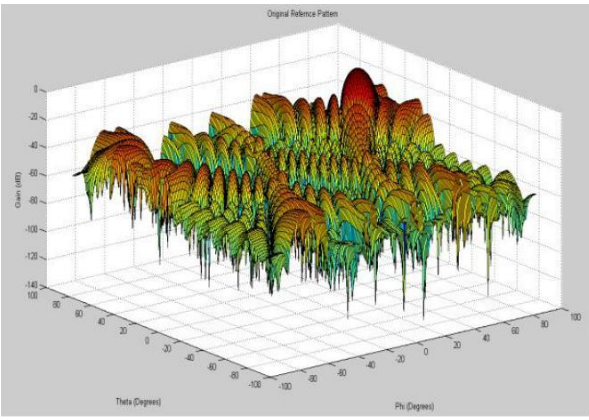
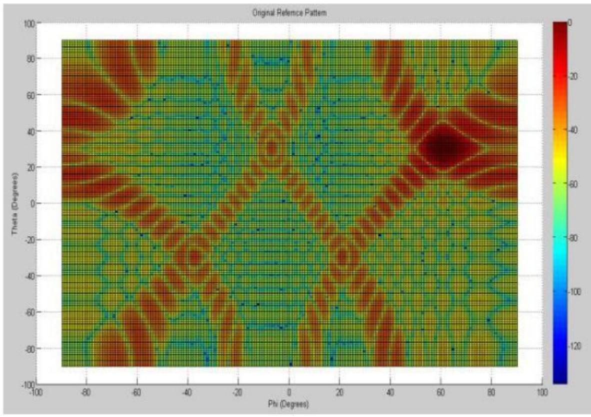


Figure 6.23: Rhombic Antenna Array

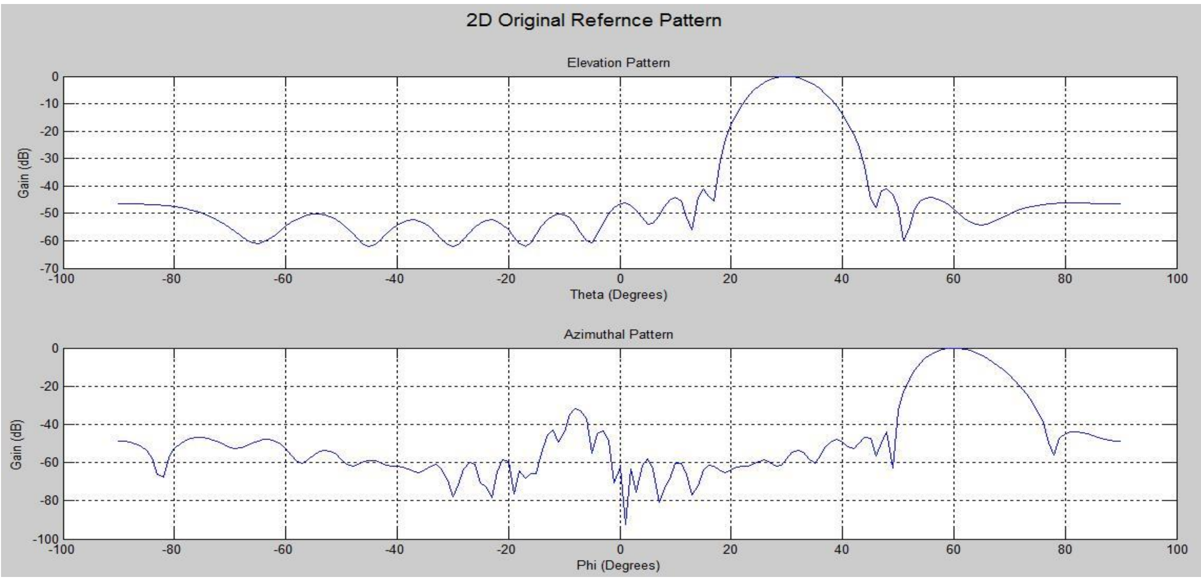
6.4.1 Taylor Reference:



(a)



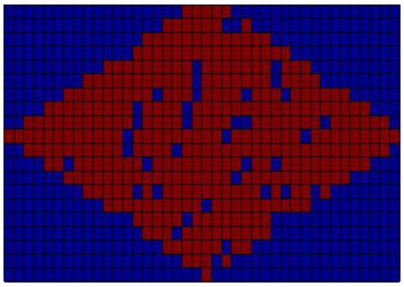
(b)



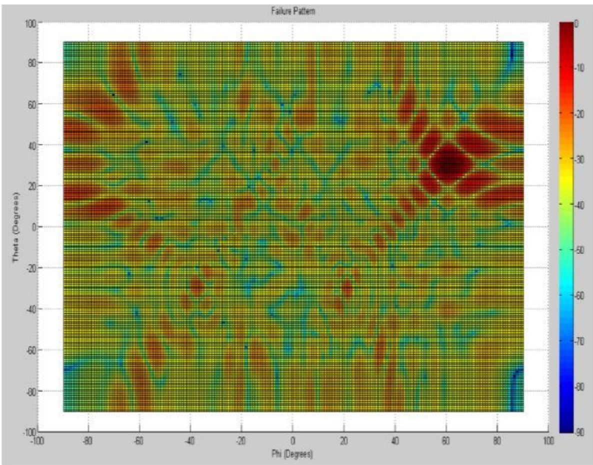
(c)

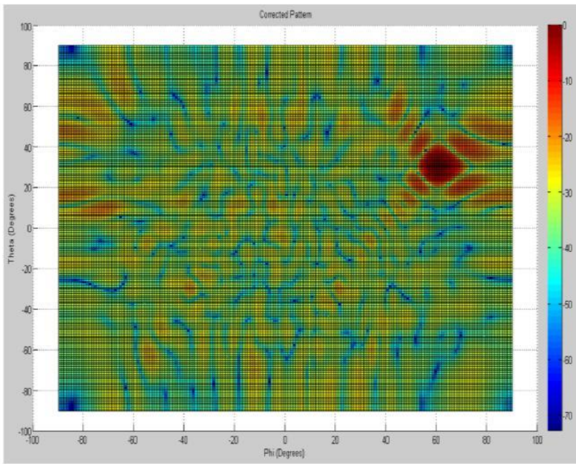
Figure 6.24: (a) Three-Dimensional Reference Pattern, (b) XY view (top view), (c) Two-Dimensional Reference pattern

6.4.2 Distributed Failure – 10%:

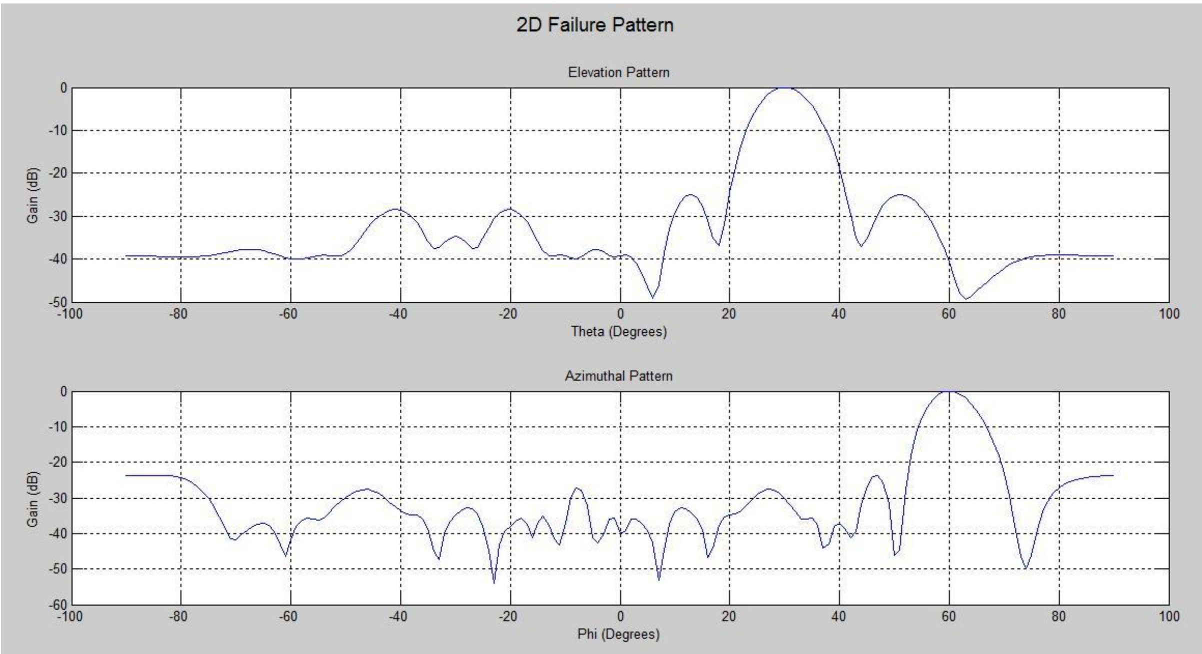


(a)

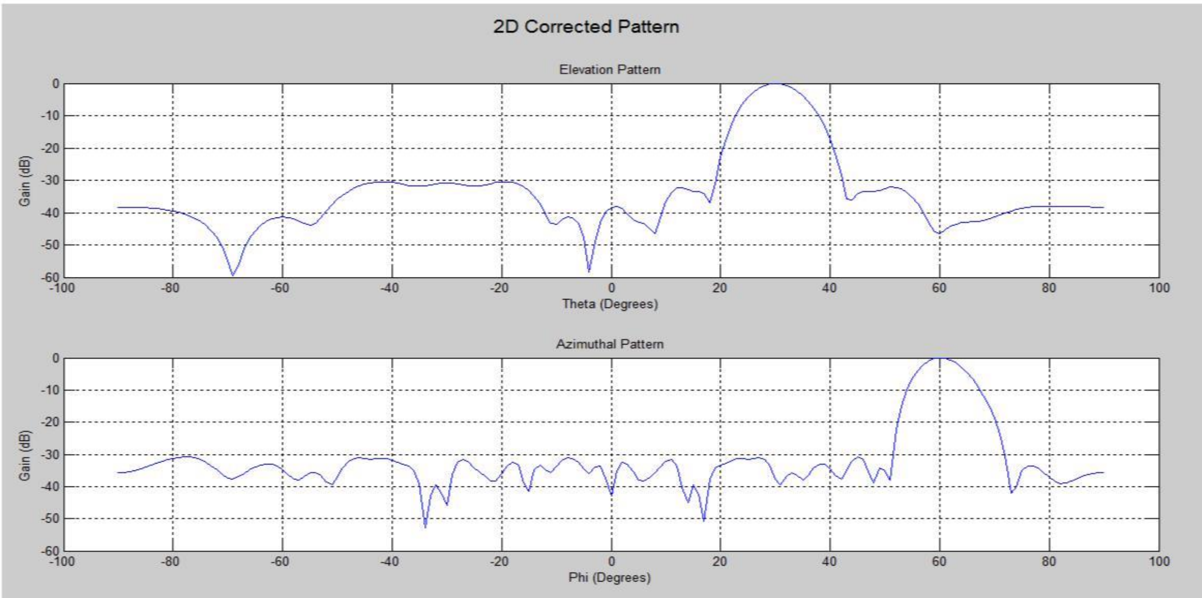




(b) (c)



(d)



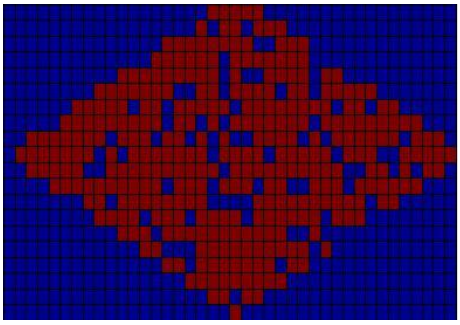
(e)

Figure 6.25: (a) Rhombic antenna array with 10% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

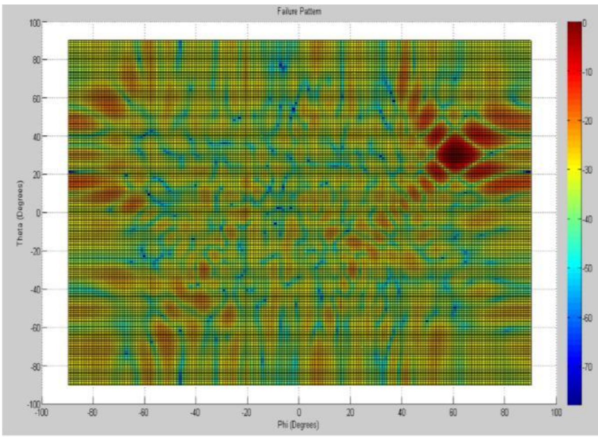
Results for 10% distributed failure in the case of rhombic antenna array are presented. Number of antenna elements failed was 42 and were found to be distributed over the entire antenna array [figure 6.25 (a)]. In the top view of failure pattern [figure 6.25 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -15dB to -35dB. In the top view of the corrected pattern [figure 6.25 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -32dB to -50dB.

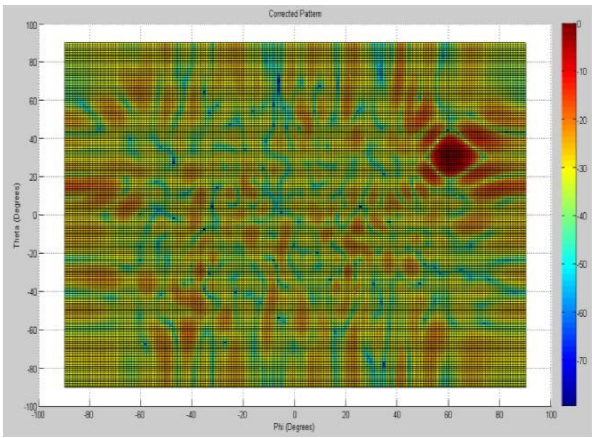
The two-dimensional failure pattern [figure 6.25 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -24.9801dB and -24.9668dB respectively in the elevation plane and -23.7501dB and -23.7984dB respectively in the azimuthal plane. The mean and of SLLs were found to be -35.6041dB and 6.1168dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -32.1856dB and -32.1493dB respectively in the elevation plane and -34.094dB and -33.5679dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.25 (e)]. The mean and of SLLs also showed values close to reference pattern, -36.9319dB and 5.21dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix D* shows the computed results.

6.4.3 Distributed Failure – 20%:

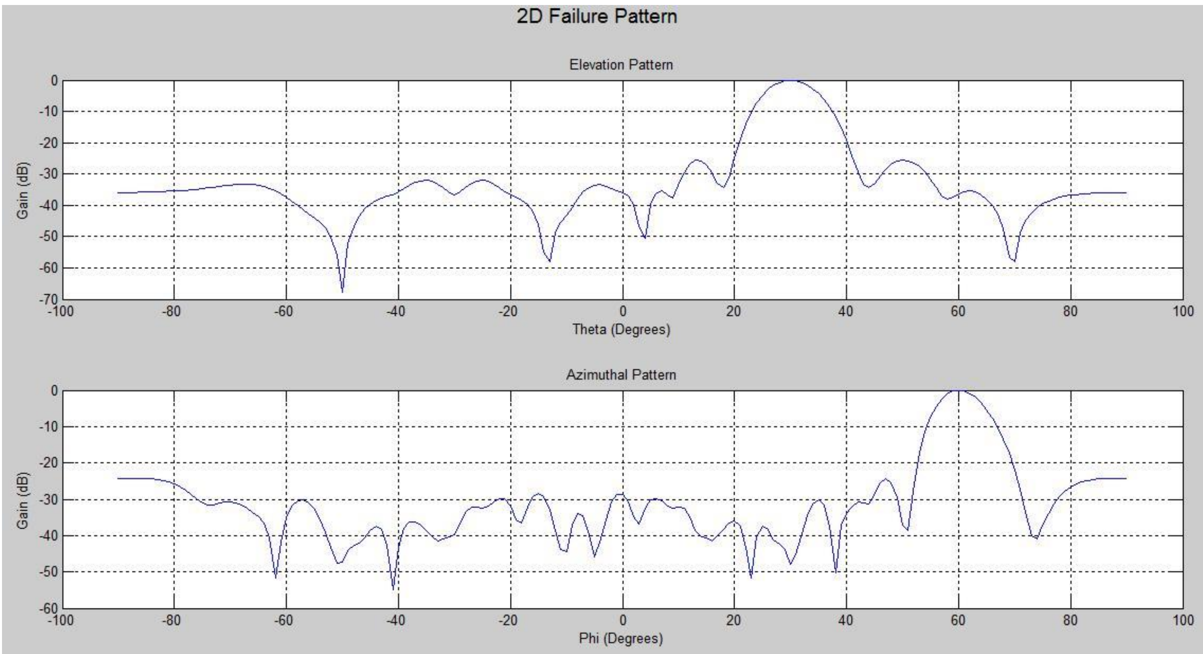


(a)

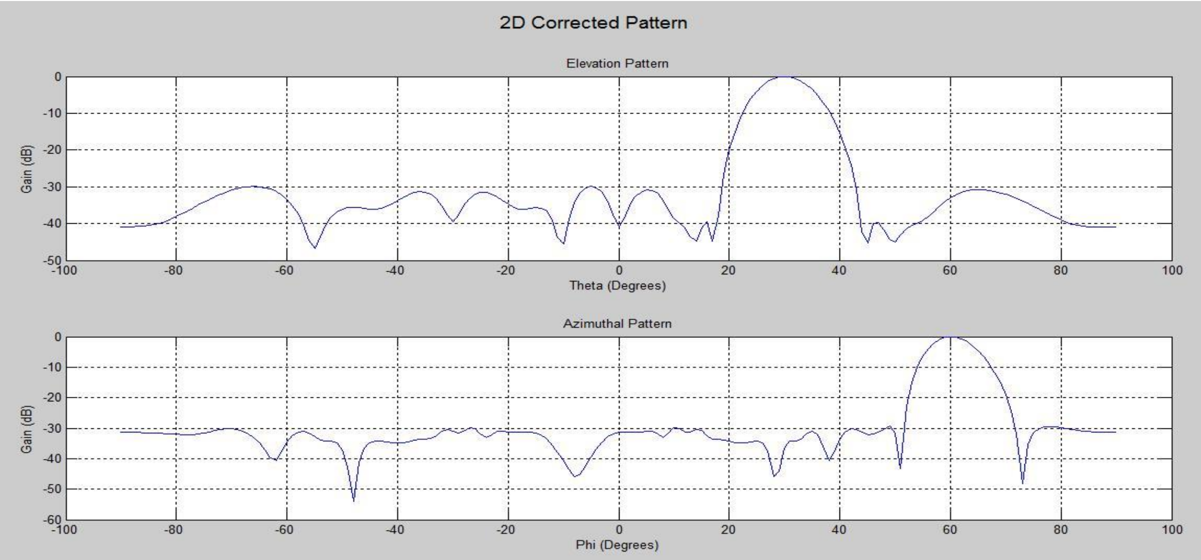




(b) (c)



(d)



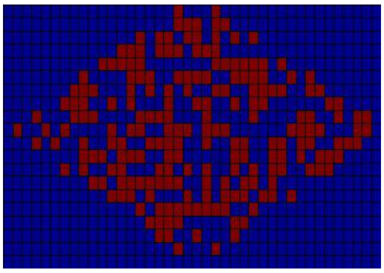
(e)

Figure 6.26: (a) Rhombic antenna array with 20% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

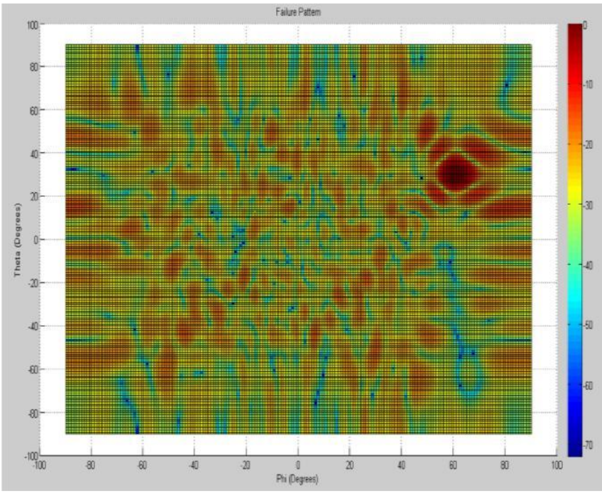
Results for 20% distributed failure in the case of rhombic antenna array are presented. Number of antenna elements failed was 84 and were found to be distributed over the entire antenna array [figure 6.26 (a)]. In the top view of failure pattern [figure 6.26 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -25dB. In the top view of the corrected pattern [figure 6.26 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -30dB to -45dB.

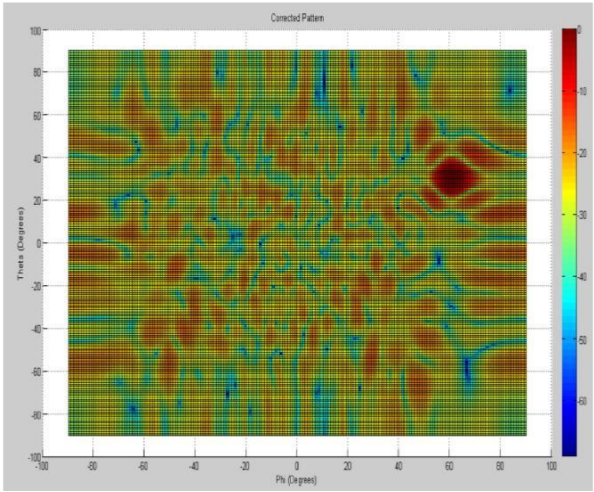
The two-dimensional failure pattern [figure 6.26 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -25.644dB and -25.5267dB respectively in the elevation plane and -24.2753dB and -24.2958dB respectively in the azimuthal plane. The mean and of SLLs were found to be -35.9119dB and 6.8416dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -39.5402dB and -39.7262dB respectively in the elevation plane and -29.4129dB and -29.4248dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.26 (e)]. The mean and of SLLs also showed values close to reference pattern, -34.7168dB and 4.1603dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix D* shows the computed results.

6.4.4 Distributed Failure – 50%:

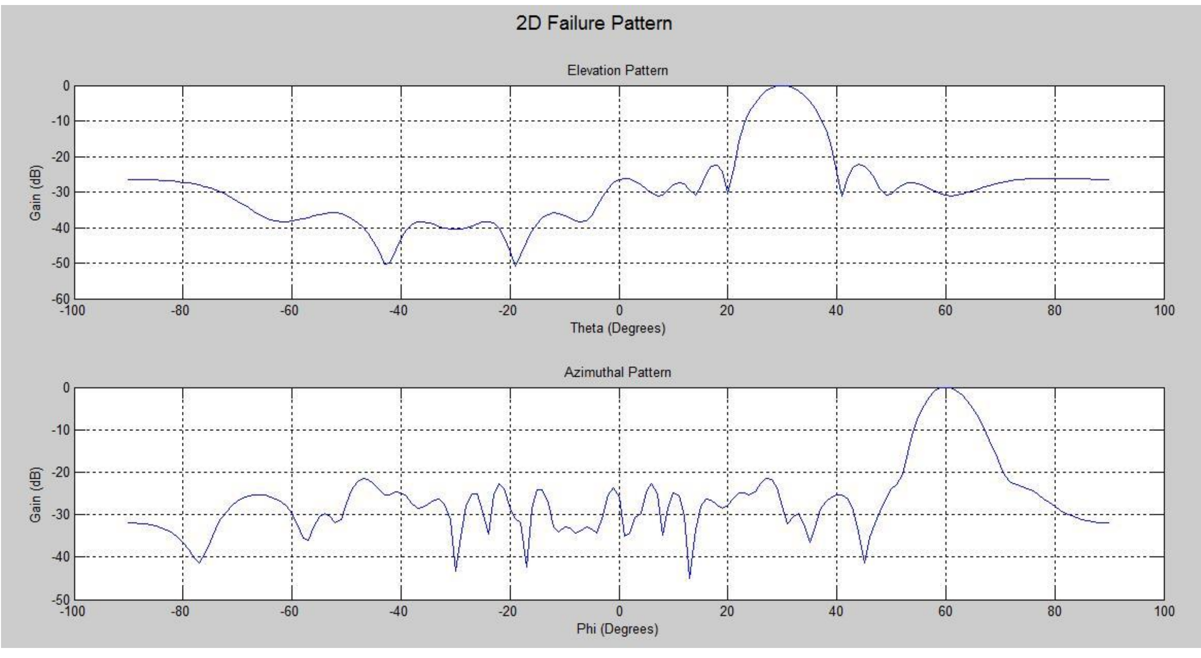


(a)

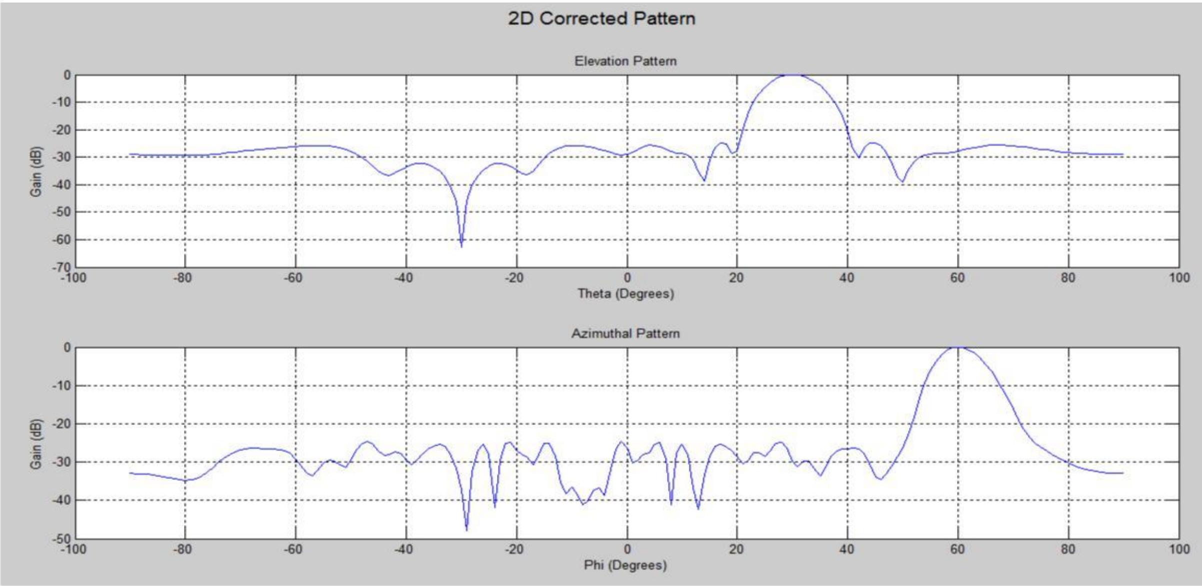




(b) (c)



(d)



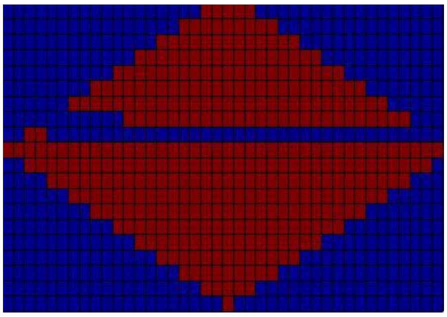
(e)

Figure 6.27: (a) Rhombic antenna array with 50% distributed failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

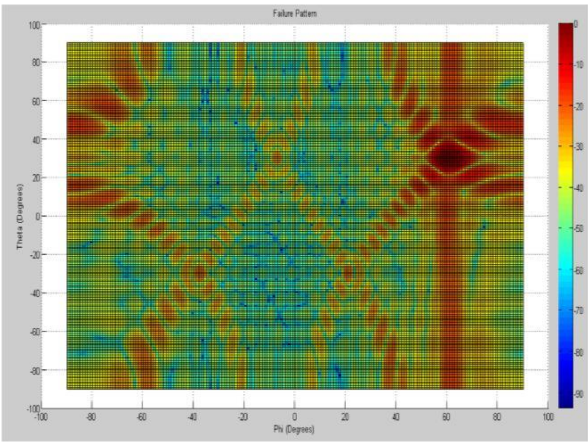
Results for 50% distributed failure in the case of rhombic antenna array are presented. Number of antenna elements failed was 211 and were found to be distributed over the entire antenna array [figure 6.27 (a)]. In the top view of failure pattern [figure 6.27 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -20dB. In the top view of the corrected pattern [figure 6.27 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -20dB to -35dB.

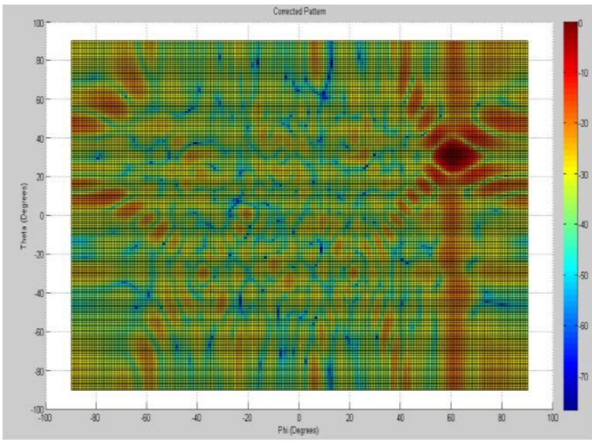
The two-dimensional failure pattern [figure 6.27 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -22.3535dB and -22.2879dB respectively in the elevation plane and -23.8407dB and -23.8303dB respectively in the azimuthal plane. The mean and of SLLs were found to be -31.2145dB and 6.0618dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -24.8099dB and -24.7867dB respectively in the elevation plane and -26.4323dB and -29.5538dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.27 (e)]. The mean and of SLLs also showed values close to reference pattern, -29.9383dB and 4.6456dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was better than failure pattern. *Appendix D* shows the computed results.

6.4.5 Concentrated Failure – 10%:

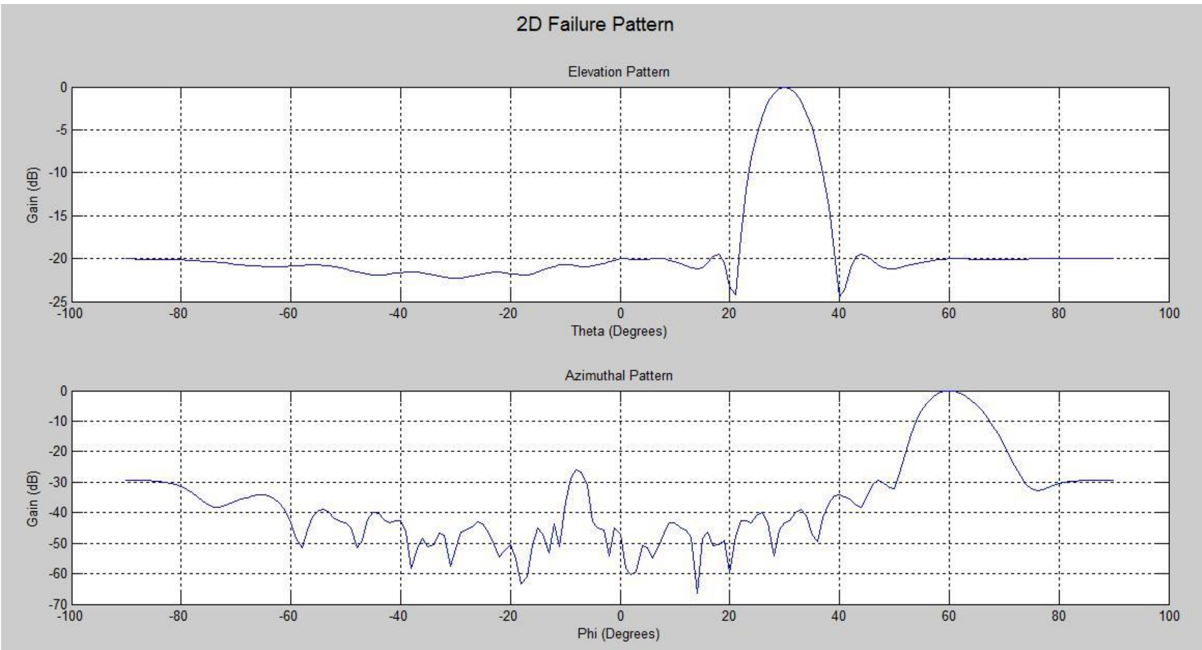


(a)

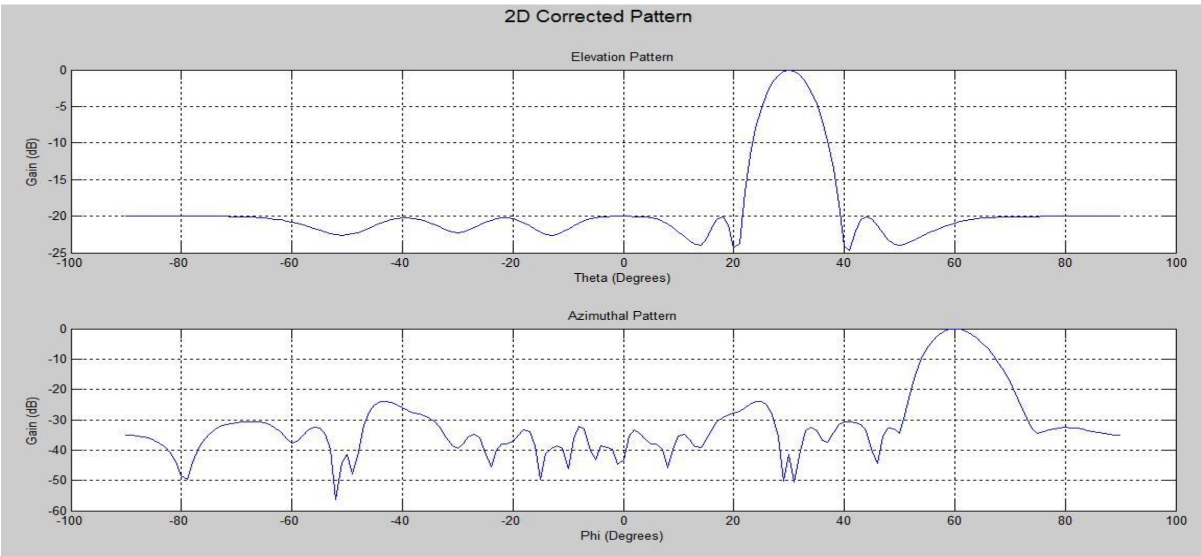




(b) (c)



(d)



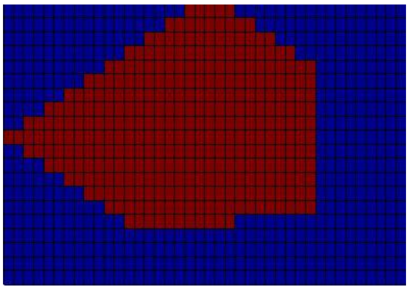
(e)

Figure 6.28: (a) Rhombic antenna array with 10% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

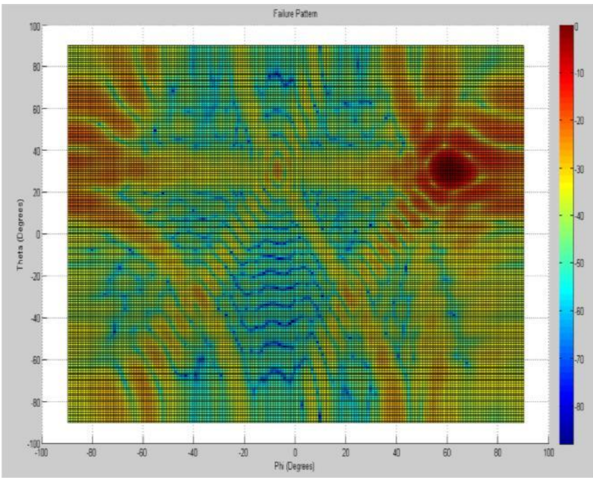
Results for 10% concentrated failure in the case of rhombic antenna array are presented. Number of antenna elements failed was 42 and were found to be concentrated over the middle region of antenna array [figure 6.28 (a)]. In the top view of failure pattern [figure 6.28 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -20dB. In the top view of the corrected pattern [figure 6.28 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -18dB to -30dB.

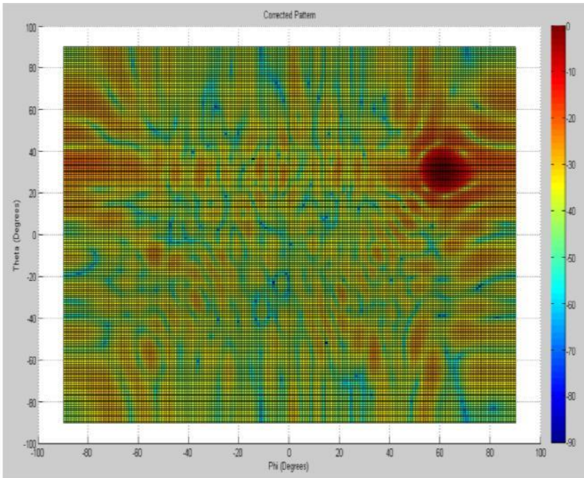
The two-dimensional failure pattern [figure 6.28 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -19.4818dB and -19.4558dB respectively in the elevation plane and -29.3912dB and -29.35dB respectively in the azimuthal plane. The mean and of SLLs were found to be -31.0022dB and 12.374dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -20.1458dB and -20.121dB respectively in the elevation plane and -32.7772dB and -32.599dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.28 (e)]. The mean and of SLLs also showed values close to reference pattern, -27.9719dB and 8.3744dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix D* shows the computed results.

6.4.6 Concentrated Failure – 20%:

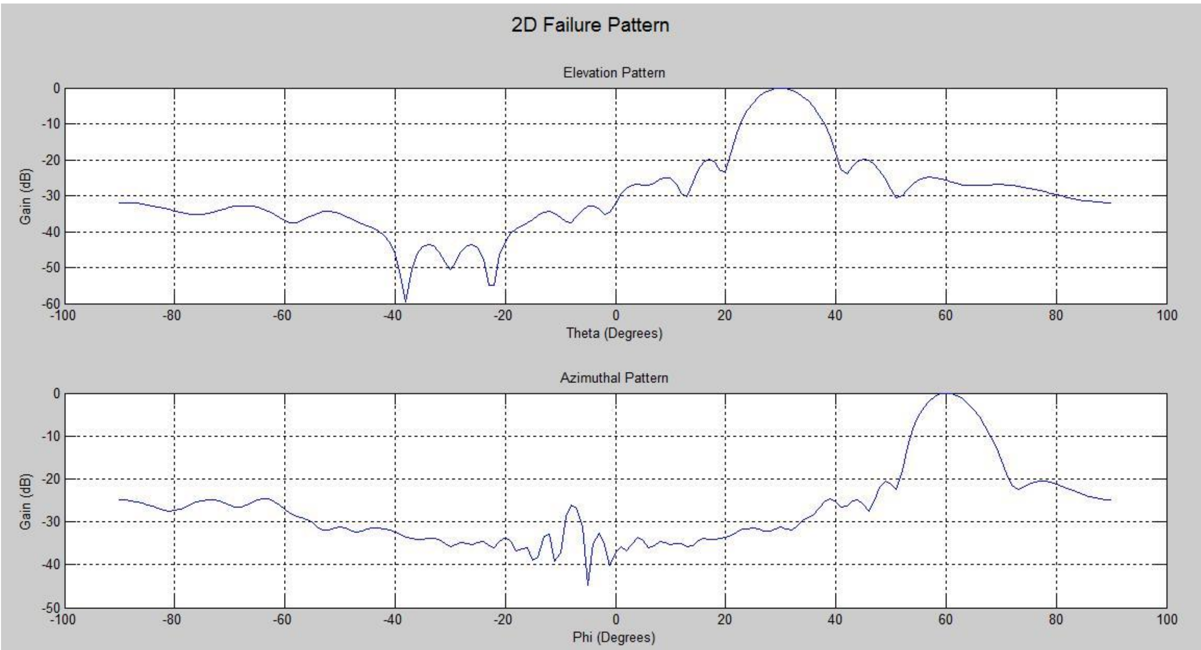


(a)

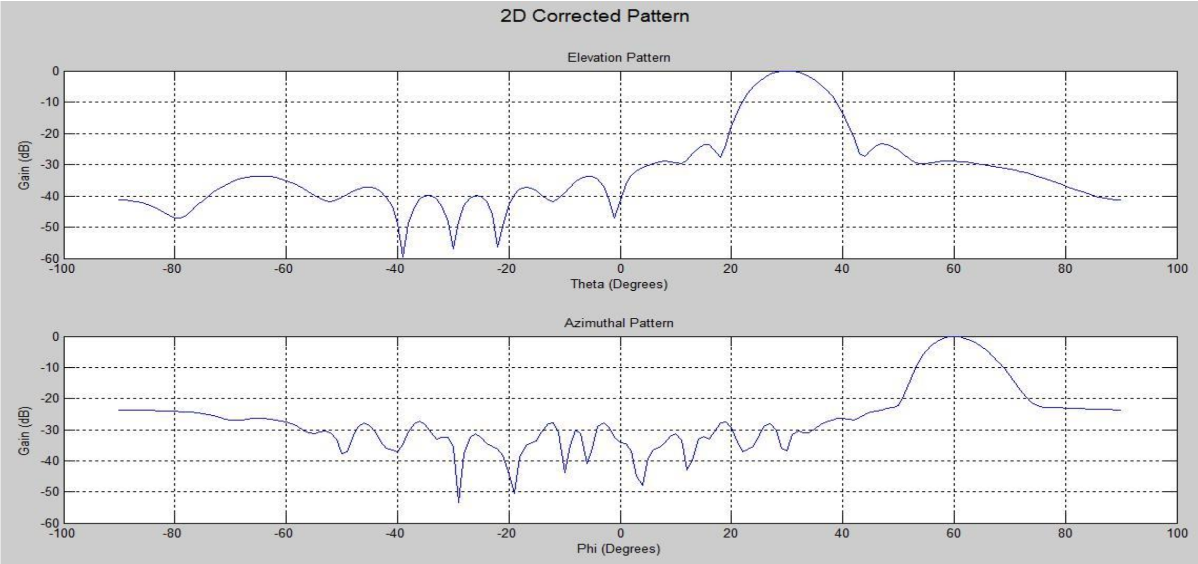




(b) (c)



(d)



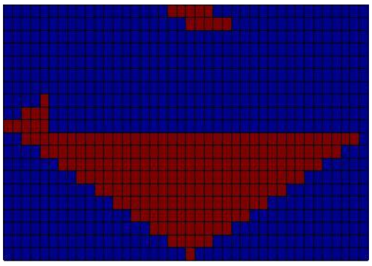
(e)

Figure 6.29: (a) Rhombic antenna array with 20% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

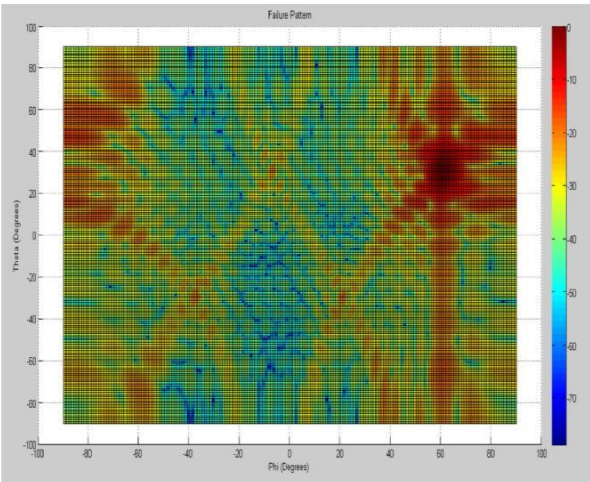
Results for 20% concentrated failure in the case of rhombic antenna array are presented. Number of antenna elements failed was 84 and were found to be concentrated over the bottom-right region of antenna array [figure 6.29 (a)]. In the top view of failure pattern [figure 6.29 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -10dB to -20dB. In the top view of the corrected pattern [figure 6.29 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -20dB to -45dB.

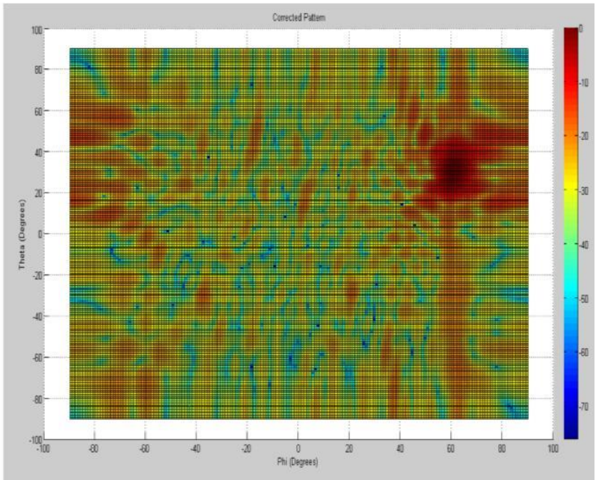
The two-dimensional failure pattern [figure 6.29 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -19.9491dB and -19.9501dB respectively in the elevation plane and -20.4966dB and -20.467dB respectively in the azimuthal plane. The mean and of SLLs were found to be -32.0008dB and 6.4767dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -23.5768dB and -23.4541dB respectively in the elevation plane and -23.1278dB and -23.0213dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.29 (e)]. The mean and of SLLs also showed values close to reference pattern, -34.6716dB and 6.8781dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was close to the reference pattern. *Appendix D* shows the computed results.

6.4.7 Concentrated Failure – 50%:

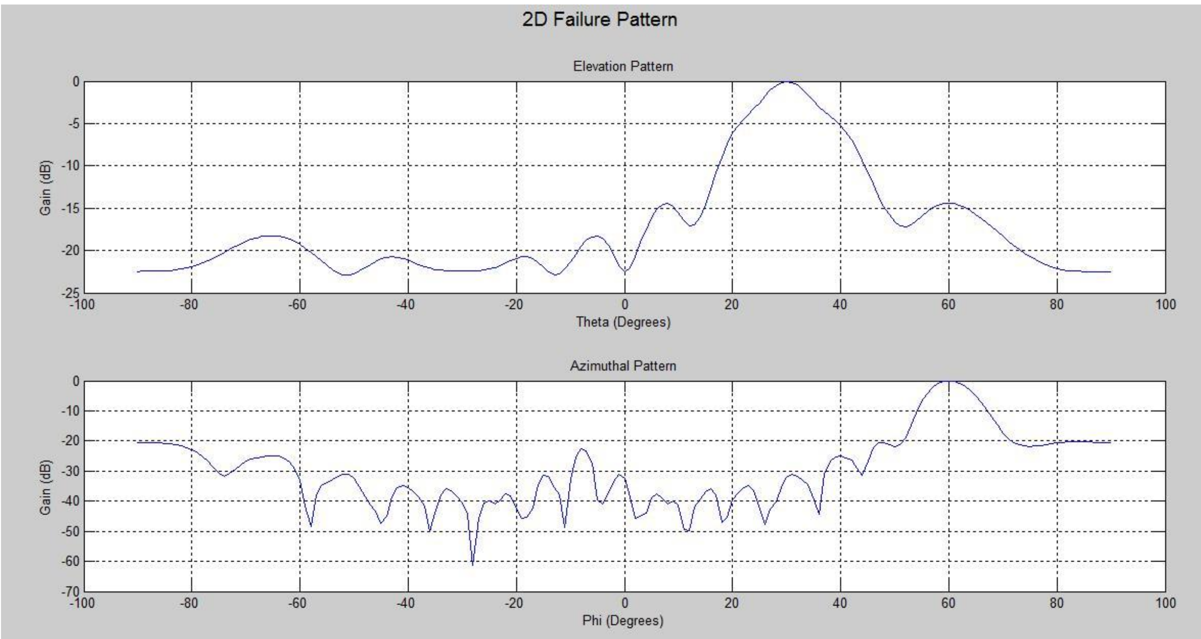


(a)

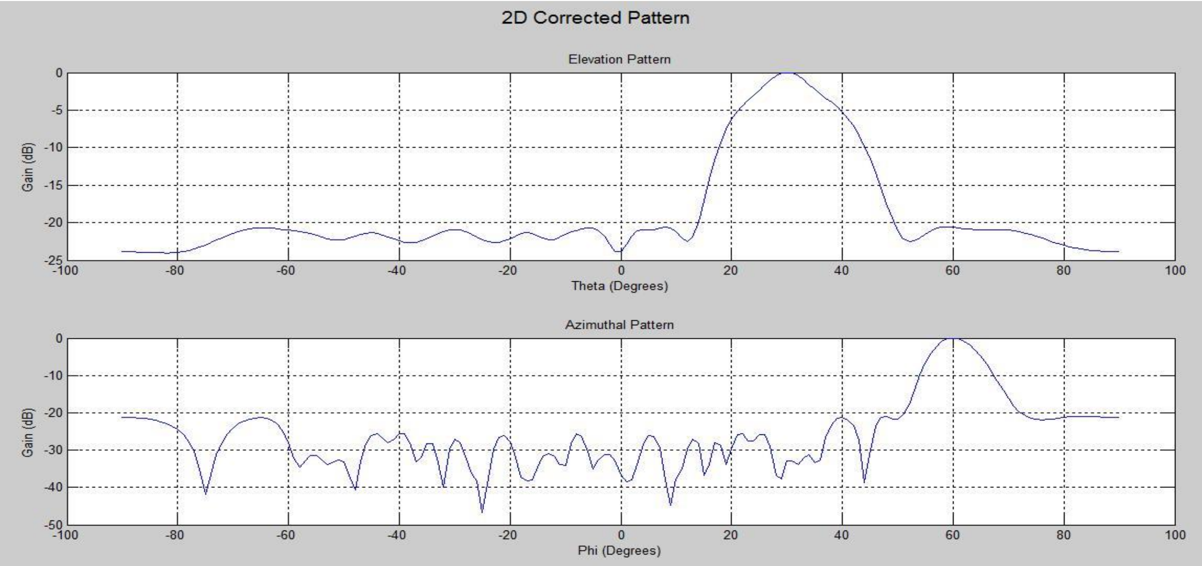




(b) (c)



(d)



(e)

Figure 6.30: (a) Rhombic antenna array with 50% concentrated failure; (b) Three-dimensional failure pattern; (c) Three-dimensional corrected pattern; (d) Two-dimensional failure pattern; (e) Two-dimensional corrected pattern

Results for 50% concentrated failure in the case of rhombic antenna array are presented. Number of antenna elements failed was 211 and were found to be concentrated over the major part of top half region of antenna array [figure 6.30 (a)]. In the top view of failure pattern [figure 6.30 (b)], the main lobe was observed at azimuthal and elevation angles of 60° and 30°, the side-lobe levels adjacent to the main lobe showed gain in the range of -5dB to -15dB. In the top view of the corrected pattern [figure 6.30 (c)], the side-lobe levels adjacent to the main lobe showed gain in the range of -20dB to -35dB.

The two-dimensional failure pattern [figure 6.30 (d)], showed an ascent of side-lobe levels adjacent to the main lobe. The gain of first left SLL and right SLL were -14.4116dB and -14.3983dB respectively in the elevation plane and -20.4053dB and -20.2966dB respectively in the azimuthal plane. The mean and of SLLs were found to be -27.3242dB and 9.3226dB respectively, indicating discrepancy. After the correction using GA, the first left SLL and right SLL were -20.5528dB and -20.5431dB respectively in the elevation plane and -21.0288dB and -20.9753dB respectively in the azimuthal plane, thus showing considerable descent [figure 6.30 (e)]. The mean and of SLLs also showed values close to reference pattern, -25.7143dB and 5.5532dB respectively. Thus, the SLL suppression from the flawed pattern was evident. The levelled side-lobes indicated that the result was an optimum solution and was better than the failure pattern. *Appendix D* shows the computed results.

6.5 INFERENCES:

- From the above results, it was found that the application of Genetic Algorithm on concentrated and distributed failures yielded better results for element failure mitigation and side-lobe level reduction in case of Distributed failure for same percentage of failure than on Concentrated failure.
- In case of concentrated failure, if the failure occurred in the central region of antenna array, GA was successful to yield a better pattern. But the pattern was not better when compared to same percentage of failure if occurred in the other regions.
- As the failure percentage increased both in case of concentrated and distributed failures, GA yielded satisfactory reduction in SLL. However, Mean and σ were found to be deviated away from the reference pattern parameter values.
- The element failure mitigation in linear array showed the reduction of SLL adjacent to Main-lobe. However, in certain cases, for the same percentage of failure, the relative level of Grating lobes after correction were found to be higher than that of failure pattern. This upheld the fact that GA was more successfully evident in element failure mitigation for planar arrays than in linear arrays.
- In all the case, the failures of 50% could be an extreme example and could be thought as the worst case. Even in such a case, the difference between the SLLs between the reference and the optimised configurations were acceptable enough in distributed failure, however not in the case of concentrated failure.
- The wider beamwidth was due to the Taylor reference pattern. The beam width also spread in the corrected pattern as the number of failed elements increase. However the spread occurred at much lower gain levels.
- From the tests so far, for any arbitrary shapes of antennas, the GA parameters were found to be dependent on the number and locations of flawed elements.
- GA was found to be dependent on the number of elements. Larger the number of elements better the performance of GA. This could be observed from the analysis of linear and planar antenna arrays, GA yielded best results for rectangle antenna array than on any other shapes.

CHAPTER 7

APPLICATIONS

CHAPTER 7: APPLICATIONS

7.1 APPLICATIONS OF GENETIC ALGORITHM:

Genetic algorithms have been used for difficult problems, for machine learning and also for evolving simple programs. They have been also used for some art, for evolving pictures and music [1]. A few applications of GA are as follows:

- Nonlinear dynamical systems–predicting, data analysis
- Robot trajectory planning
- Evolving LISP programs (genetic programming)
- Strategy planning
- Finding shape of protein molecules
- TSP and sequence scheduling
- Functions for creating images
- Control–gas pipeline, pole balancing, missile evasion, pursuit
- Design–semiconductor layout, aircraft design, keyboard configuration, communication networks
- Scheduling–manufacturing, facility scheduling, resource allocation
- Machine Learning–Designing neural networks, both architecture and weights, improving classification algorithms, classifier systems
- Signal Processing–filter design
- Combinatorial Optimization–set covering, traveling salesman (TSP), Sequence scheduling, routing, bin packing, graph coloring and partitioning
- Computing – Operating systems, gaming

7.2 APPLICATIONS OF 'GA ON ELEMENT FAILURE MITIGATION':

The possibility of failure correction for antenna arrays provides a cost-effective alternative to hardware replacement which might be too late or too time-consuming, especially for arrays performing critical operations, such as, for instance, in the battlefield [25]. Some of the target applications are:

- ARGOS, GMDSS, INMARSAT and other satellite tracking and telemetry
- Automatic Vehicle Location (AVL)
- Broadcast: Television and Radio
- Cable Television, Wireless (MMDS)
- Cellular Radio
- Global Positioning System (GPS)
- Local and Wide Area Networks, Wireless (LAN/WAN)
- Marine Communications and Navigation
- Military Communications and SATCOM
- Portable Wireless Products
- Radio Frequency Identification (RFID)
- Supervisory Control And Data Acquisition (SCADA)
- Spread Spectrum Devices
- Transportation Systems (IVHS, Automatic Toll Systems, etc.)

CHAPTER 8

FUTURE WORK

CHAPTER 8: FUTURE WORK

- Particle swarm optimization (PSO) is a population based stochastic optimization technique, inspired by social behaviour of bird flocking or fish schooling [1]. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. It could be demonstrated that PSO will get better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications.

- Use of Genetic Algorithm for Jammer suppression.

- Implementation of Genetic Algorithms for element failure mitigation on FPGA/ASIC and other real-time systems.

- Use of Genetic Algorithm for calibration of the antenna arrays.

CONCLUSION

CONCLUSION:

The element failure in active antenna array hampered its performance. The pattern of this handicapped antenna was analysed and the pattern showed the unacceptable rise in the SLLs. The Genetic Algorithm scheme proposed was found to be suitable for providing a cost-effective alternative for the hardware replacement like that of a software patch.

The possibility of compensation of SLL increase due to the failure of array elements was a reality due to the evolutionary characteristics of the Genetic Algorithm. Antenna array with defected elements has shown to provide better SLL after the proposed scheme, with respect to predefined radiation pattern characteristics even in the case of large number of failed elements and for any arbitrary antenna array shape.

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APPENDIX

APPENDIX:

APPENDIX A: LINEAR ANTENNA ARRAY – COMPUTED RESULTS

Linear Antenna Array

S.N.	Antenna Case Study	Failure Percentage		HPBW (degree)	NNBW (degree)	Left Side Lobe		Right Side Lobe		Main Lobe Level (dB)	Side Lobe Level (dB)	
						Power Level (dB)	Location Degree	Power Level (dB)	Location Degree		Mean (dB)	Standard Deviation (dB)
1	Without Failure			3.7504	14	-35.6533	-8	-35.6533	8	21.4788	-43.2244	8.4917
2	Distributed Failure	10%	Without Correction	2.639	6	-13.2197	-5	-13.2197	5	31	-24.6621	5.8012
3			With Correction	3.4928	14	-26.6584	-9	-26.6584	9	15.9505	-28.9383	2.8432
4		20%	Without Correction	2.6262	6	-13.254	-5	-13.254	5	28	-22.868	5.6159
5			With Correction	3.6884	10	-24.5006	-6	-24.5006	6	13.9787	-27.5954	5.0907
6		50%	Without Correction	2.6826	6	-12.558	-5	12.558	5	17	-16.5511	4.6853
7			With Correction	2.9454	6	-12.7693	-5	-12.7693	5	7.8269	-16.7129	5.0262
8	Concentrated Failure	10%	Without Correction	2.8084	8	-16.2114	-8	-16.2114	8	31	-27.2928	8.1254
9			With Correction	4.0748	12	-22.0535	-7	-22.0535	7	19.7388	-31.3046	6.3979
10		20%	Without Correction	2.3638	6	-6.4664	-5	-6.4664	5	28	-27.727	10.8788
11			With Correction	2.8882	6	-11.6941	-5	-11.6941	5	7.6336	-15.7758	3.6406
12		50%	Without Correction	5.263	14	-11.8131	-11	-11.8131	11	17	-22.2558	5.1193
13			With Correction	8.6854	28	-33.5536	-15	-33.5536	15	9.3116	-37.4331	3.1849

APPENDIX B: RECTANGULAR ANTENNA ARRAY – COMPUTED RESULTS

Rectangular Antenna Array

S.N.	Antenna Case Study	Failure Percentage		Angular Cut	HPBW (degree)	NNBW (degree)	Left Side Lobe Power Level (dB)	Left Side Lobe Location Degree	Right Side Lobe Power Level (dB)	Right Side Lobe Location Degree	Main Lobe Level (dB)	Side Lobe Level (dB) Mean (dB)	Side Lobe Level (dB) Standard Deviation (dB)
1	Without Failure	Not Applicable		Elevation	7.2791	21	-34.6957	19	-35.0215	43	50.21774846	-42.2595647	8.85357323
				Azimuthal	6.4923	19	-34.8966	51	-34.7321	73			
2	Distributed Failure	10%	Without Correction	Elevation	5.4929	12	-13.4785	21	-13.5444	40	57.786	-28.6514	7.4337
				Azimuthal	4.8166	11	-13.7632	53	-13.7526	69			
3			With Correction	Elevation	7.1862	21	-32.0833	19	-32.4657	42	49.7132	-36.9321	4.7832
				Azimuthal	6.3961	19	-30.6104	51	-30.6393	73			
4		20%	Without Correction	Elevation	5.5049	12	-13.1002	21	-13.1537	40	56.7644	-28.5404	6.8559
				Azimuthal	4.928	11	-14.8583	53	-14.8397	69			
5			With Correction	Elevation	6.8759	19	-27.3058	20	-26.8169	42	49.3102	-33.7851	5.4299
				Azimuthal	6.2887	18	-28.7693	51	-28.8197	72			
6		50%	Without Correction	Elevation	5.4809	12	-13.7169	21	-13.6976	39	52.6694	-27.4871	6.0804
				Azimuthal	4.9169	11	-12.9355	53	-12.6498	70			
7			With Correction	Elevation	6.314	16	-22.0798	21	-21.9052	41	46.5955	-30.2272	6.5037
				Azimuthal	5.8853	15	-21.8118	52	-21.6005	71			
8	Concentrated Failure	10%	Without Correction	Elevation	5.9425	14	-15.7534	21	-15.7337	40	57.786	-29.1302	7.0872
				Azimuthal	4.8961	11	-13.8587	53	-13.8486	69			
9			With Correction	Elevation	7.5493	21	-28.9291	18	-28.8515	44	50.475	-36.298	6.0816
				Azimuthal	6.3566	18	-29.9851	51	-29.5813	72			
10		20%	Without Correction	Elevation	6.241	14	-13.3672	20	-13.3184	41	56.7644	-28.6493	7.6898
				Azimuthal	5.4323	13	-13.518	52	-13.5787	71			
11			With Correction	Elevation	7.552	19	-24.4363	19	-24.4515	43	49.6753	-35.0615	6.1354
				Azimuthal	6.7196	18	-24.6211	51	-24.4851	73			
12		50%	Without Correction	Elevation	4.6058	9	-4.762	22	-4.6659	38	52.6694	-21.3975	8.3293
				Azimuthal	4.5601	10	-8.64	53	-8.6435	69			
13			With Correction	Elevation	5.3381	11	-8.5447	22	-8.5646	38	44.2791	-20.6674	6.9915
				Azimuthal	5.0768	11	-9.0279	52	-8.8479	70			

APPENDIX C: HEXAGONAL ANTENNA ARRAY – COMPUTED RESULTS

Hexagonal Antenna Array

S.N.	Antenna Case Study	Failure Percentage		Angular Cut	HPBW (degree)	NNBW (degree)	Left Side Lobe		Right Side Lobe		Main Lobe Level (dB)	Side Lobe Level (dB)	
							Power Level (dB)	Location Degree	Power Level (dB)	Location Degree		Mean (dB)	Standard Deviation (dB)
1	Without Failure	Not Applicable		Elevation	7.6769	26	-35.5891	15	-35.5026	48	49.5048	-52.003	15.8625
				Azimuthal	7.3308	21	-25.9467	50	-25.6423	76			
2	Distributed Failure	10%	Without Correction	Elevation	6.1969	15	-20.7152	21	-20.6448	40	55.2235	-34.3778	7.1952
				Azimuthal	6.2715	16	-17.1146	51	-17.1352	73			
3			With Correction	Elevation	7.4623	21	-33.123	18	-32.4559	43	49.1238	-37.4881	4.9967
				Azimuthal	7.1849	21	-29.8814	50	-29.886	75			
4		20%	Without Correction	Elevation	6.1859	15	-19.9032	21	-19.8348	40	54.2023	-32.0507	6.4402
				Azimuthal	6.2528	15	-16.2635	51	-16.2925	73			
5			With Correction	Elevation	7.4648	21	-31.5974	19	-31.3451	43	48.2506	-33.5476	5.2124
				Azimuthal	7.0008	19	-24.4201	50	-24.396	74			
6		50%	Without Correction	Elevation	6.117	15	-18.7581	21	-18.7047	40	50.103	-28.2615	5.7395
				Azimuthal	6.2455	16	-18.5597	51	-18.5079	72			
7			With Correction	Elevation	6.6273	17	-21.9294	20	-21.9434	42	45.9645	-27.6726	4.8541
				Azimuthal	6.6701	18	-22.5742	51	-22.4476	73			
8	Concentrated Failure	10%	Without Correction	Elevation	5.9255	14	-16.2478	21	-16.2471	40	55.2235	-30.9386	7.7579
				Azimuthal	7.1216	17	-15.3523	50	-15.3543	75			
9			With Correction	Elevation	6.8336	19	-29.5503	20	-29.5172	42	50.5474	-33.2474	5.7687
				Azimuthal	7.8088	21	-21.5004	49	-21.4101	77			
10		20%	Without Correction	Elevation	5.9141	14	-14.6054	21	-14.609	40	54.2023	-30.9107	6.4367
				Azimuthal	7.5049	21	-21.8206	48	-21.8161	81			
11			With Correction	Elevation	6.6714	17	-23.5013	20	-23.5423	41	49.7842	-32.3075	6.2917
				Azimuthal	8.0698	24	-23.8519	48	-23.7102	84			
12		50%	Without Correction	Elevation	10.3617	24	-13.6891	14	-13.643	49	50.103	-28.228	6.7498
				Azimuthal	6.9161	16	-15.1344	50	-15.1327	75			
13			With Correction	Elevation	11.8297	25	-14.1861	15	-14.1915	48	43.8834	-29.4925	6.4484
				Azimuthal	7.9098	21	-21.3039	49	-21.2895	78			

Appendix D: Rhombic Antenna Array – Computed Results

Rhombic Antenna Array

S.N.	Antenna Case Study	Failure Percentage		Angular Cut	HPBW (degree)	NNBW (degree)	Left Side Lobe		Right Side Lobe		Main Lobe Level (dB)	Side Lobe Level (dB)	
							Power Level (dB)	Location Degree	Power Level (dB)	Location Degree		Mean (dB)	Standard Deviation (dB)
1	Without Failure	Not Applicable		Elevation	9.3025	29	-41.0343	15	-41.1489	48	47.8304	-54.52	8.1991
				Azimuthal	8.1981	29	-43.8656	48	-43.9196	81			
8	Distributed Failure	10%	Without Correction	Elevation	8.2459	26	-24.9801	13	-24.9668	51	51.5728	-35.6041	6.1168
				Azimuthal	6.9084	23	-23.7501	47	-23.7984	90			
9			With Correction	Elevation	8.5647	25	-32.1856	13	-32.1493	51	48.6221	-36.9319	5.21
				Azimuthal	7.501	22	-34.094	49	-33.5679	77			
10		20%	Without Correction	Elevation	8.1523	26	-25.644	13	-25.5267	50	50.5526	-35.9119	6.8416
				Azimuthal	6.977	22	-24.2753	47	-24.2958	88			
11			With Correction	Elevation	8.9265	28	-39.5402	16	-39.7262	47	46.806	-34.7168	4.1603
				Azimuthal	7.4879	22	-29.4129	49	-29.4248	78			
12		50%	Without Correction	Elevation	8.097	21	-22.3535	18	-22.2879	44	46.4444	-31.2145	6.0618
				Azimuthal	7.2222	19	-23.8407	50	-23.8303	75			
13			With Correction	Elevation	8.4225	22	-24.8099	17	-24.7867	45	43.8585	-29.9383	4.6456
				Azimuthal	7.6458	27	-26.4323	41	-29.5538	79			
2	Concentrated Failure	10%	Without Correction	Elevation	7.7757	19	-19.4818	18	-19.4558	44	51.5728	-31.0022	12.374
				Azimuthal	7.3887	24	-29.3912	47	-29.35	87			
3			With Correction	Elevation	7.8909	19	-20.1458	18	-20.121	44	48.187	-27.9719	8.3744
				Azimuthal	7.4171	35	-32.7772	48	-32.599	80			
4		20%	Without Correction	Elevation	8.7777	22	-19.9491	17	-19.9501	45	50.5526	-32.0008	6.4767
				Azimuthal	8.1949	22	-20.4966	49	-20.467	77			
5			With Correction	Elevation	9.679	25	-23.5768	15	-23.4541	47	47.0237	-34.6716	6.8781
				Azimuthal	8.7297	23	-23.1278	48	-23.0213	80			
6		50%	Without Correction	Elevation	11.5951	40	-14.4116	8	-14.3983	60	46.4444	-27.3242	9.3226
				Azimuthal	7.1427	24	-20.4053	48	-20.2966	84			
7			With Correction	Elevation	12.1081	40	-20.5528	8	-20.5431	59	42.6524	-25.7143	5.5532
				Azimuthal	7.3118	20	-21.0288	48	-20.9753	83			

APPENDIX E: MATHWORKS MATLAB

MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation. Using the MATLAB product, you can solve technical computing problems faster than with traditional programming languages, such as C, C++, and FORTRAN.

You can use MATLAB in a wide range of applications, including signal and image processing, communications, control design, test and measurement, financial modeling and analysis, and computational biology. Add-on toolboxes (collections of special-purpose MATLAB functions, available separately) extend the MATLAB environment to solve particular classes of problems in these application areas.

MATLAB provides a number of features for documenting and sharing your work. You can integrate your MATLAB code with other languages and applications, and distribute your MATLAB algorithms and applications. Features include:

- High-level language for technical computing
- Development environment for managing code, files, and data
- Interactive tools for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration
- 2-D and 3-D graphics functions for visualizing data
- Tools for building custom graphical user interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages, such as C, C++, Fortran, Java™, COM, and Microsoft® Excel®

APPENDIX F: TAYLOR WINDOW

Syntax:

w = taylorwin(n)

w = taylorwin(n,nbar)

w = taylorwin(n,nbar,sll)

Description:

Taylor windows are similar to *Chebyshev* windows. While a Chebyshev window has the narrowest possible main lobe for a specified side-lobe level, a Taylor window allows you to make trade-offs between the main lobe width and side-lobe level. The Taylor distribution avoids edge discontinuities, so Taylor window side-lobes decrease monotonically. Taylor window coefficients are not normalized. Taylor windows are typically used in radar applications, such as weighting synthetic aperture radar images and antenna design.

w = taylorwin(n) returns an n-point Taylor window in a column vector w. The values in this vector are the window weights or coefficients. n must be a positive integer. The default value for the number of approximately equal height side-lobes (nbar) is 4 and for the maximum side-lobe level (sll) is -30.

w = taylorwin(n,nbar) returns an n-point Taylor window with nbar nearly constant-level side-lobes adjacent to the main lobe. These side-lobes are "nearly constant-level" because some decay occurs in the transition region. nbar must be a positive integer.

w = taylorwin(n,nbar,sll) returns an n-point Taylor window with a maximum side-lobe level of sll dB relative to the main lobe peak. sll must be a negative value, such as -30, which produces side-lobes with peaks 30 dB down from the main lobe peak.