Summer 2010

A Differential Absorption Model for Remote Sensing of Atmospheric Pressure

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A DIFFERENTIAL ABSORPTION MODEL FOR REMOTE SENSING OF ATMOSPHERIC PRESSURE

By

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B.S. May 2008, Old Dominion University

A Thesis Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

COMPUTER ENGINEERING

OLD DOMINION UNIVERSITY

August 2010

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ABSTRACT

The goal of the project is to develop and test a "model based" radar processing strategy that is compatible with the concept of a "cognitive radar". The basic approach will be to develop a cognitive radar algorithm (genetic algorithm) based on the capabilities of an existing commercially available Software Radio. While the focus of this effort is the development of a candidate approach for genetic algorithm, the longer term goal would be to implement the approach using this software radio technology to provide a low cost radar processor. The proposed technology would use differential absorption radar working at the 50-56 GHz O_2 absorption band to estimate the surface level pressure. At these radar wavelengths, the reflection of the radar-echo from water surfaces is strongly attenuated by atmospheric column O_2. Due to the uniform mixture of O_2 gases within the atmosphere, the total atmospheric column O_2 is proportional to atmospheric path lengths and the total atmospheric column air, and thus, to surface barometric pressures. A radar system that covers these wavelengths will have great potential for weather observations and other meteorological applications.

ACKOWNLEDGEMENTS

I would like to thank Dr. Roland Wes Lawrence for his guidance and efforts as my thesis director. I am also very grateful for his encouragement throughout the undergraduate years. I would like to thank Dr. Zia-ur-Rahman and Dr. Linda Vahala for their valuable time and consideration in serving on my thesis committee. Finally, I would like to thank my family and friends for all their support.

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CHAPTER 1

INTRODUCTION

Air pressure is one of the most important parameters regularly measured at surface meteorological stations. With developments of remote sensing methods, especially in airborne and satellite remote sensing techniques, large-scale and global surface pressure measurements significantly lag behind other important parameters, such as surface temperature. Researchers have suggested using satellite oxygen A-band methods (both passive and active) to measure the pressure [1][2][3][4]. The active instruments rely on the operation of complicated highly stable laser systems on a space platform and are thus technically difficult, while passive methods are restricted to daytime measurements and areas of low cloud cover. Thus, there are still no real remote sensing measurements of surface pressure, even in experimental stages. This study considers active microwave techniques at strong O_2 absorption bands (around 50–56-GHz) for the remote sensing of surface air pressure. At these frequencies, the total extinction of radar echoes from surfaces is strongly correlated with the amount of O_2 in the atmosphere, atmospheric path lengths and surface air pressures [10].

Flower and Peckham studied the possibility of a microwave pressure sounder using active techniques [5]. A total of six channels covering frequencies from 25-75GHz were considered. A major problem observed in using this wide spectral region is the significant additional dependence on microwave absorption by liquid water (L), clouds and atmospheric water vapor (V).

Format for this thesis follows the *IEEE Transaction on Computers.*

Atmospheric and cloud water temperatures also have different effects on the absorptions at different frequencies. The complexity in matching footprints of the six different wavelength channels makes their system even more challenging [5]. To overcome these obstacles, researchers have considered a novel technique that uses the absorption difference from the echoes of dual-frequency O_2-band radar to estimate the surface pressure [10]. The approach is to use two frequency channels with very similar L and V absorption characteristics and footprints because of the minimal spectral separation between channels [10]. The microwave absorption effects due to L and V should be effectively removed from the ratio of reflected radar signals of the two channels. Thus, the difference in attenuation (in dB) between the two frequencies will be a nearly linear function of the barometric pressure [10]. Simulated results suggested that the accuracy of surface air pressure estimations using this approach may be comparable to conventional *in-situ* buoy measurements [10]. The regional scale pressure measurements over the ocean that may be enabled by the above radar concept are important for many applications and would be particularly useful for weather forecasting and tropical storm predictions [10].

1.1 Pressure Measurements for Hurricane Forecasts

An important application of large area pressure field data was illustrated by Xiao et al.[20] The landfall of Hurricane Fran, (1996) was modeled by Xiao et al. using a region weather model to provide a predicted three-day track of the hurricane. The track prediction was simulated for three cases. First, the control case including no surface pressure data, then two cases where the surface pressure fields are assumed (generated after the fact) with spatial sampling of 18 and 54 km. The results of these simulations are shown in Figure 1.1, adapted from Xiao [20] and Lin [21]. The three-day predictions using pressure data and calculated wind field showed improved landfall predictions relative the control prediction using only the standard model without pressure data [20]. The addition of calculated pressure and wind fields to the model, with spatial sampling of

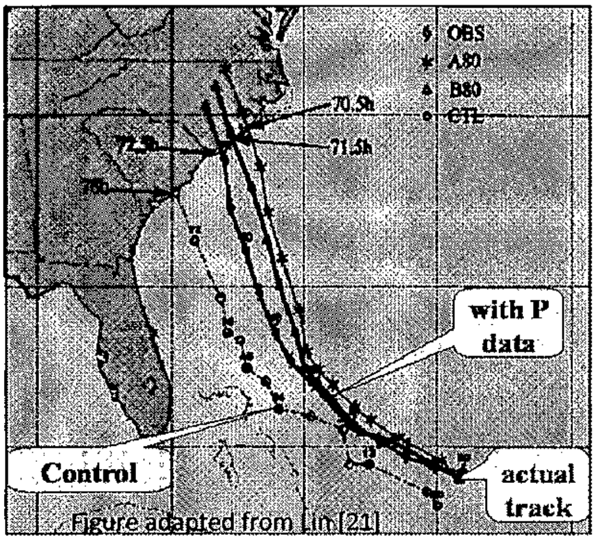

Figure 1.1 Improved landfall predictions possible with moderate pressure field data from [20].

54km (A80 curve) and 18km (B80 curve) reduced the predicted landfall error from about 350 km to approximately 170 and 100 km for 54 and 18 km spatial sampling respectively. The hurricane intensity predictions were also improved by the addition of the pressure fields. These more accurate predictions could improve hurricane preparation and evacuation planning and reduce the loss of property and life due to severe storms. The radar concept suggested by Lin [10] could be flown on a manned or unmanned aircraft to provide the pressure field with spatial sampling consistent with the simulation discussed above, and could lead to improved hurricane predictions.

Researchers at the NASA Langley Research Center have developed a prototype of differential radar and performed flight tests onboard a helicopter over the Chesapeake

Bay to verify the measurement approach. The radar return power was measured in 11 bands between 50 and 60 GHz for altitudes of 1000 to 5000 ft. Attenuation data from these flights for 2000, 3000, and 5000 ft altitudes are shown in Figure 1.2. The increased attenuation as the frequency is increased, partially due to the increased attenuation due to O_2, can be seen in the Figure. The increased attenuation with increasing frequency will be a function of the barometric pressure. The basic measurement approach described in [10] is to measure the difference in loss (in dB) between two frequencies. Changes in this differential loss ratio are then expected to be nearly linear with respect to barometric pressure.

The larger the separation in frequency of the loss measurements, consistent with assumption that attenuation due to water vapor and surface scattering is similar for the two frequencies, the more sensitive the differential loss ratio will be to barometric pressure.

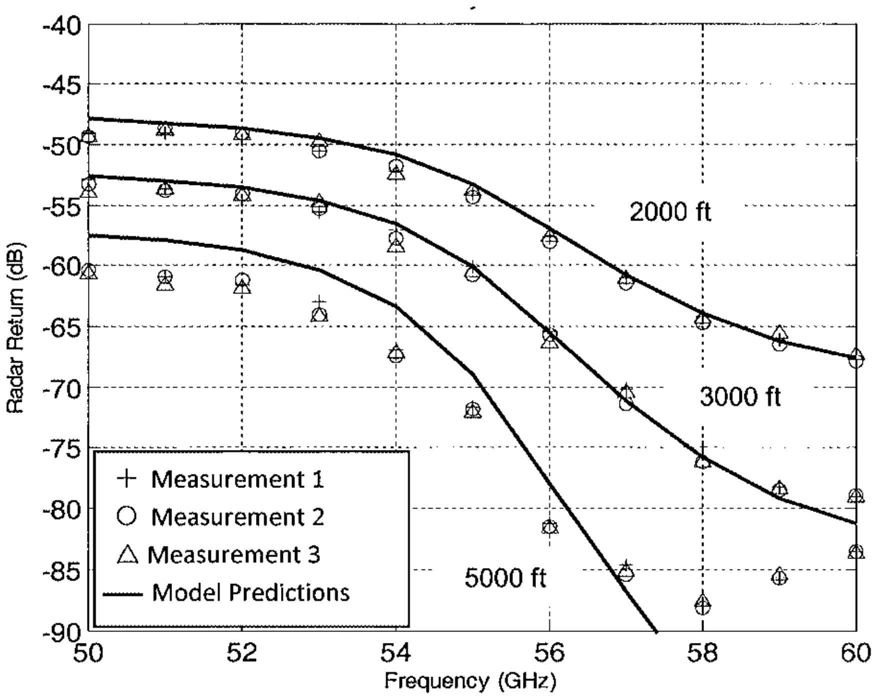

Figure 1.2 Measured radar loss for NASA prototype radar.

However, these initial flight tests highlighted several important performance limitations of the radar. Figure 1.2 illustrates the impact of the noise floor of the radar at 5000 ft. For an altitude of 5000 ft the signal-to-noise ratio (SNR) is poor above about 56 GHz due to the increased attenuation. That is, the rapid increase in O_2 attenuation above 56 GHz limits the ability of the radar to perform the required loss measurements. This loss will also increase with increasing barometric pressure. Thus, a frequency that has an acceptable SNR for a low barometric pressure may be unacceptable for higher pressures. In addition, changes in the surface roughness of the sea surface will also affect the radar return power. This suggests that the operational radar should adapt the measurement frequency to the changing measurement environment to optimize the surface pressure retrieval.

An approach is, thus, needed that can provide real time estimation of the mean and variance of the surface pressure and provide feedback to the radar to modify the measurement frequency to minimize the variance of the surface pressure estimate. An algorithm must, therefore, be developed to estimate the surface level pressure as a function of the differential atmospheric loss. The algorithm should find the best surface temperature and surface level pressure for the loss measured by the radar. This research will develop a search algorithm based on the concept of genetic evolution to estimate surface pressure and temperature from the radar differential loss measurements.

These search algorithms, typically called, Genetic Algorithms (GA) are probabilistic search techniques frequently applied to difficult optimization and learning problems. They involve modeling the characteristics of the solution as genes and sets of these genes as solutions to the problem. The optimization of the solution is then attempted using the idea of the evolution of a gene pool in which inheritance and mutation occur. The principle of "survival of the fittest" is also modeled in the pool's evolution as the GA progresses. The approach here is to treat the atmospheric properties, in particular surface level pressure and temperature, as genes and use a model for atmospheric absorption to allow the GA to find the best fit to the radar measurements. Further, the algorithm will provide feedback to adjust the radar frequency to optimize the surface level pressure measurement.

1.2 Characteristics of the Problem

In this application, the GA must estimate the surface pressure from aircraft radar measurements as the aircraft flies over storms. A prototype radar concept has been developed to demonstrate the measurement concept [19]. To demonstrate the GA, the requirements were developed based on this prototype radar and theoretical modeling for aircraft altitude of 20 km. The GA should update the radar frequency approximately every second to adjust for changes in atmospheric loss and surface scattering and provide an estimate of the surface level pressure every 500 ms [10]. For this application, the GA must converge to a best fit for the surface pressure within 500 ms and be able to track the changes in the surface pressure.

Several important challenges for the pressure retrieval should be mentioned. The atmospheric absorption model, or forward model, developed to compute the atmospheric loss at a particular frequency is computationally very expensive. As a result, the speed of the GA is significantly affected if implemented in the conventional manner of evaluating each individual in the population. Since the goal is to develop a real time estimate of the surface pressure and temperature from the radar measurements, the speed of convergence of this approach would not likely be sufficient for our application. Thus, rapid convergence of the GA is an important feature for our application.

In addition, for the surface pressure retrieval, the reference for the GA is the differential atmospheric loss measured by the radar. Thus, the truth-value, used to determine the best individuals includes measurement noise, due to the SNR of the radar, and varies with the changes in surface level pressure. The GA should be able to track the changes in the truth-value and find an optimal solution for the corresponding radar measurement. As will be discussed, conventional implementations of the GA are not well suited to meet these goals and necessitated modifications in implementation of the mutation and crossover techniques that are used in the evolution of the GA.

A discussion of earlier research in the development of GA techniques is provided in Chapter 2. Chapter 3 includes a discussion of the proposed GA and an application of this algorithm to a simple curve fit problem to illustrate the characteristics and optimization of the algorithm. A description of the microwave atmospheric absorption model used to simulate the radar measurements and to evaluate the fitness of individuals in presented in Chapter 4. Chapter 4 also includes a discussion of modification to the GA developed for the O_2 radar application.

CHAPTER 2
LITERATURE REVIEW

Early research in the development of Genetic Algorithms treated the genes as binary in nature. Binary GA is normally used for applications where each gene in the individual is a binary bit (0 or 1). Operations to modify sequences of genes, or individuals, were borrowed from genetics and included splicing bits from different genes or inverting a bit in a particular location. Other researchers generalized these concepts to include 'analog' genes. Analog GA operates on individuals whose genes are real numbers. When applied to analog genes the techniques used for genetic manipulation must be modified. For example, gene splicing may be replaced by weighted averages of genes from two individuals, and mutation may occur by inverting a bit from '1' to '0' may be replaced by adding a random number to the gene. For this application, an analog GA was selected, since the population consists of individuals whose genes are real numbers representing the surface level pressure and temperature. A detailed study of different methods used for the implementation of the GA has been performed. A brief discussion of some of the possible methods of implementation is presented below.

A genetic algorithm begins with a collection of solutions to the problem under consideration. This collection is known as the *population*. A fitness value is associated with each individual in the population. The fitness value indicates how good a solution the individual is to the problem. The fitness values can be defined differently for different applications. In general, the larger the fitness value, the better the solution. However, in this application the fitness value is defined as the distance between the radar measured differential loss and the model prediction for the genes of the individual. With this definition, the better the solution is the lower the difference in the measured and estimated loss parameters. At start-up the initial population is generated and the fitness value of each individual in the population is calculated by measuring the difference in the radar measurement and the O_2 radar model estimate. The algorithm then iterates through a series of operations that progressively improves the quality of the solution. These steps typically include the use of selection, crossover, and mutation to generate the next population, and then ranking the new population based on the fitness values. A brief description of these operations is given below.

2.1 Basic GA Operations

The selection, or cloning, operation propagates an individual from the present generation, to the next generation based on its fitness values. The selection process can be carried forward in a number of ways such as the roulette wheel, stochastic uniform, or one can write one's own selection function. In the roulette wheel method, the fittest individual has the largest share of the roulette wheel. Individuals are selected by a "spin" of the roulette wheel and the fitter individuals will have a better chance of survival. The stochastic uniform method, on the other hand, lays out a line in which each parent corresponds to a section of the line of length proportional to its scaled value. The algorithm moves along the line in steps equal to the inverse of the number of individuals to be selected. A uniformly distributed random number determines the location with-in the step and the algorithm selects a parent at each step. In any case, the solution with a better fitness value is most likely to be selected to propagate to the next generation. The individuals selected or cloned by these operations are essentially a set of the best-fit solutions to the problem and are moved directly to the next generation. The cloning operation ensures that the best-fit individuals are moved to the next generation and thus encourage the convergence of the algorithm. However, if used in excess, these operations may reduce the genetic diversity and the GA will not reach a global optimum.

In the crossover process, a certain number of randomly chosen pairs from the present generation have their genetic material combined to create a new pair of solutions (children) that inherit the characteristics from both the parents and are then placed in the new population. The crossover operations provide the opportunity for the genes from two individuals to be combined to form a new individual in the next generation. The new individual will generally have different genes than the parents creating genetic diversity.

The mutation operation provides random variation to the genes of individuals in the population. A portion of the individuals in the new generation is randomly chosen to undergo mutation. This process perturbs the gene pool and introduces new solutions. Mutation operations make small random changes to individuals in the population, which provide genetic diversity and enables the GA to search a broader solution space. This process is carried out to prevent the GA from converging too rapidly to a non-global solution.

The new individuals created using the above processes are used to form the next generation. The fitness value of each individual is calculated and then the individuals are sorted according to their fitness value with the best individuals being ranked the highest. The above processes are repeated on the set of the best individuals to create subsequent generations. One complete run through the above steps is called a *generation* and a new population is created at the end of each generation which is equal in size to the starting population. This new population is used as the starting population for the next generation. The algorithm iterates until either a certain number of generations has been completed or a certain quality of the solution has been obtained.

Many researchers have studied and presented various methods to implement GA to perform optimization of the solution to a problem. One of the most difficult challenges is processing large sets of data and optimizing a large population to converge to an optimal solution within an acceptable time for real world implementations and still maintain the accuracy of the algorithm. Many approaches have been developed to reduce the time required for GA to reach an acceptable solution in applications where the fitness evaluation required for the problem under consideration is computationally expensive. A successful GA will typically include genetic manipulations to ensure rapid convergence, as well as operations to avoid early convergence to a local optimum. Some of the approaches are discussed below.

2.2 Existing Methods

2.2.1 Genetic algorithm with cluster analysis

In GA with cluster analysis approach, the range of all genes is normalized between 0 and 1 and the fitness of each individual is computed. The distance between the individuals is then computed based on the normalized genes, and nearby individuals are grouped into clusters. The fitness of each cluster, defined as the average fitness of all individuals within the cluster, is then evaluated along with the average fitness of the entire population. The clusters whose fitness values are lower than the average for the population are then discarded. The next generation is formed and the cluster analysis is repeated.

This method eliminates individuals based on average fitness of their cluster rather than their individual fitness and gives priority to promising regions in the solution space rather than individuals. It is guaranteed to produce the global optimum and works well when the model is not computationally expensive since fitness for each individual needs to be evaluated at each generation [8]. This approach is not a good fit for this study's application since the fitness of all individuals within a cluster must be calculated each generation and the forward model, where the atmospheric loss is computed, is computationally very expensive. This approach may converge rapidly in terms of number of generations needed to reach an acceptable solution but the time taken for each generation is very large. Using this approach for the application would be very time consuming and not meet the goal of convergence within 500 ms.

2.2.2 Selective mutation

Most population-based, reproductive, optimization algorithms such as the GA, ant colony optimization, and particle swarm optimization share a common problem namely, premature convergence [7]. The individuals in a premature convergence situation get stuck at some local optimum and are unable to propagate out of the region around the local optimum. This problem occurs when highly fit parents in a population pool breed many similar offspring in the early generations. If the highly fit individuals are near the local optimum, then newly generated offspring from the parents are also near the local optimum.

The crossover operation, one of the operations of GAs, may not generate off-spring sufficiently different from their parents to escape the local optimum because it uses only existing genetic information. Therefore, crossover is regarded as a convergent operation. This issue can be addressed by adding diversity to the population which will enable the GA to explore a more diverse solution space (individuals) and better converge to a global optimum. Since diversity can be added to the population using the mutation function, mutation is known as an exploratory operation.

If the exploration power, the diversity in the population, is increased by setting the mutation probability high, then the speed of convergence to global optimum is usually reduced. This considerably degrades the performance of the GA for real-time applications. Therefore, the selective mutation method is used to address this issue [7]. It is assumed that if an individual has low fitness, then it is far from the global optimum. Thus, the gene with the most significant impact on fitness is mutated to improve its fitness. Whereas if an individual has high fitness, then we regard it to be near the global optimum and mutate the least significant genes [7]. As a result, this selective mutation allows genetic algorithms to increase their rate of convergence while avoiding areas of local optimum.

Although this method helps find a global optimum relatively quickly, this method is not suited well to this study's application as the application does not really have two distinct areas that impact the individual differently.

2.3 Types of Crossover

As discussed earlier, crossover is basically an approach to create a new individual ("child") from two successful "parents" by combining the genetic material from the parents. This operation provides both convergence since the genes used were highly ranked, and exploration, since the combination of genes may be new. Crossover can be implemented in the following ways.

2.3.1 Scattered Crossover

The scattered crossover method generates a random binary vector, and selects the genes from the first parent where this vector has a value of '1', and the genes from the second parent where the vector has a value of '0.' It then combines the selected genes to form the child, **C**. For example, let us consider two parents $\mathbf{P_1}$ and $\mathbf{P_2}$:

$$\mathbf{P_1} = [a\ b\ c\ d\ e\ f\ g\ h]$$

$$\mathbf{P_2} = [1\ 2\ 3\ 4\ 5\ 6\ 7\ 8].$$

The random binary vector **R** generated by the scattered crossover method is:

$$\mathbf{R} = [1\ 1\ 0\ 0\ 1\ 0\ 0\ 0].$$

Since **R** has a '1' at positions 1, 2 and 5, the new individual-the child, **C**-will have the genes from $\mathbf{P_1}$ at locations 1, 2 and 5 and the genes from $\mathbf{P_2}$ at the other locations, resulting in the individual:

$$\mathbf{C} = [a\ b\ 3\ 4\ e\ 6\ 7\ 8]$$

This child thus adds diversity to the population and helps the GA converge to the optimal solution.

2.3.2 Single Point Crossover

The single point crossover method generates a random integer 'x' between 1 and number of genes, n, in an individual: ($1<x<n$). It selects the vector entries that are numbered less than or equal to the random number 'x' from the first parent and selects genes that are numbered greater than 'x' from the second parent. It then concatenates these entries to form the child. So, if we have two parents and each parent has n=8 genes, then let

$$\mathbf{P_1} = [\text{a b c d e f g h}]$$

$$\mathbf{P_2} = [1\ 2\ 3\ 4\ 5\ 6\ 7\ 8]$$

A random integer 'x' with a uniform distribution between 1 and 8 is generated which determines the number of genes to be inherited. Suppose that x=3. Then the child, **C**, thus formed will have the identity

$$\mathbf{C} = [\text{a b c}\ 4\ 5\ 6\ 7\ 8]$$

This is similar to scattered crossover method adding diversity to the population. However, if we add too much diversity to the population, we increase the time it takes to converge to the optimum solution. Therefore, if the genes of the parent chosen for crossover are close to the optimum we might end up choosing the genes that are far away from the optimum thereby delaying the process of converging to the optimum value.

2.3.3 Two Point Crossover

The two-point crossover method is similar to the one point crossover method discussed above. The only difference is that this method generates two random integers, 'x' and 'y' instead of one. The algorithm selects genes numbered less than or equal to x from the first parent, selects genes numbered from $x+1$ to y from the second parent, and selects genes numbered greater than y from the first parent. The algorithm then concatenates these genes to form a single gene. For example, for the set of parents

$$\mathbf{P_1} = [\mathrm{a\ b\ c\ d\ e\ f\ g\ h}]$$

$$\mathbf{P_2} = [1\ 2\ 3\ 4\ 5\ 6\ 7\ 8]$$

And random crossover points x= 3, y=6, the child **C** is

$$\mathbf{C} = [\mathrm{a\ b\ c}\ 4\ 5\ 6\ \mathrm{g\ h}]$$

2.3.4 Heuristic

The heuristic method creates children that randomly lie on the line containing the two parents, a small distance away from the parent with the better fitness value, $\mathbf{P_B}$ in the direction away from the parent with the worse fitness value, $\mathbf{P_W}$. It is a crossover operator that uses the fitness values of the two parents to determine the direction of the search. The offspring are created according to the following equations:

$$\mathbf{C_1} = \mathbf{P_B} + \mathbf{r}\ (\mathbf{P_B} - \mathbf{P_W})$$

$$\mathbf{C_2} = \mathbf{P_B}$$

where, r is a random number between 0 and 1, and $\mathbf{C_1}$ and $\mathbf{C_2}$ are the two offspring.

It is possible that $\mathbf{C_1}$ will not be viable. This can happen if r is chosen such that one or more of its genes fall outside of the allowable upper or lower bounds. For this reason, heuristic crossover has a user-defined parameter, n for the number of times to try and find an r that results in a feasible chromosome. If a feasible chromosome is not produced after n tries, the $\mathbf{P_W}$ is returned as $\mathbf{C_1}$.

2.3.5 Arithmetic Crossover

Arithmetic crossover creates children that are an arithmetic mean of two parents, $\mathbf{P_1}$ and $\mathbf{P_2}$ uniformly on the line between the parents. This method linearly combines two parent chromosome vectors to produce two new offspring according to the following equations

$$\mathbf{C_1} = a\,\mathbf{P_1} + (1- a)\,\mathbf{P_2} \tag{1}$$

$$\mathbf{C_2} = (1-a)\ \mathbf{P_1} + a\,\mathbf{P_2} \tag{2}$$

where a is a uniformly distributed random number.

Therefore, the arithmetic method of crossover predominantly uses the available data instead of exploring outliers to add diversity to the population. Thus, this approach is known as a convergent method.

Some of the above mentioned techniques for crossover do not work very well when applied to real numbers. Also, most of them like scattered, single-point and two-point methods only consider a part of the parents for crossover. The method of crossover used in the application outlined in this thesis is similar to the arithmetic approach except that each offspring is produced using the formula in equation 1 rather than using both equations 1 and 2. The way crossover is implemented in the algorithm is that it first generates a random number between 0 and 1. Using that as a multiplication factor, the genes of both the parents $\mathbf{P_1}$ and $\mathbf{P_2}$ are combined to create a child which would have the better genes from both parents. The fitness value of the child so created is computed and the child is added to the population for further crossover operations. A key aspect that the custom crossover function borrows from the heuristic approach is that one of the parents is always from the top 10% of the population and the other parent can be chosen randomly from the population. This ensures that one parent has a better fitness value while the other has a random fitness value to add more diversity to the population and avoid convergence on a local optimum.

2.4 Mutation

Mutation, as discussed earlier, is a key aspect of the GA as it prevents premature convergence and helps find the global optimum. This process perturbs the gene pool by introducing new solutions. Mutation functions make small random changes to individuals in the population which provide genetic diversity and enable the GA to search a broader space. The two most commonly used methods for mutation are discussed below.

2.4.1 Gaussian Mutation

The Gaussian mutation method adds a random number to each vector entry of an individual. This random number is taken from a Gaussian distribution with a zero mean. The standard deviation of this distribution can be controlled with two parameters. The **scale** parameter determines the standard deviation at the first generation. The **shrink** parameter controls how the standard deviation shrinks as generations evolve. Thus, the shrink parameter controls how the number of mutations decreases as a function of the generation number. This approach may not be useful for the application in this study since the GA must continually adapt to a changing truth-value so some diversity is needed even after the population "converges".

2.4.2 Uniform Mutation

Uniform mutation is a two-step process. First, the algorithm selects a fraction of the genes of an individual for mutation, where each gene has the same probability of being mutated. In the second step, the algorithm replaces each selected entry by a random number selected uniformly from the range for that entry.

The uniform mutation method essentially discards the mutated gene. Thus, the mutation tends to explore the entire solution space rather than the neighborhood around the individual. This would add to the diversity of the population but increase the time taken by the GA to converge to the optimum solution which is the essential feature for our application. Uniform mutation may work well for converging to a global optimum but once the GA converges and begins tracking changes in the truth-value different diversity may be needed to better track the change.

2.4.3 Modifications

The mutation method needed to be modified to suit the application. A custom defined mutation function modeled on the Gaussian method was used for the application. The individuals to be mutated are chosen randomly by the GA and the number of individuals to be mutated can be modified using a variable. The mutation function generates a Gaussian random number with a zero mean and the standard deviation equal the standard deviation for that gene in the population. This randomly generated number is then added to the gene to be mutated. Thus, as the algorithm converges on the optimum value the standard deviation decreases thereby decreasing the amount of mutation for each gene. Therefore, as generations increase and population converges to the optimum value, the variation to genes of individuals due to mutation is reduced. In order to maintain the global search attribute of uniform mutation, some individuals with randomly generated genes could be added to each generation. To accomplish this and maintain a constant population size some of the worst fit individuals are deleted and random individuals are added to the population. This provides more flexibility allowing rapid convergence and ensures sufficient diversity.

Before adding the complexity of the atmospheric loss model, the GA was applied to a simple curve fit test case. This test case was used to evaluate the performance of the mutation operation described above and demonstrate the GA. The crossover function used is essentially the arithmetic crossover method described earlier. Using these modifications a test GA was developed to experiment with the function of the modified crossover and mutation methods.

CHAPTER 3

DEVELOPMENT OF THE GENETIC ALGORITHM

Using the modification to the GA discussed in the previous chapter, a model was developed to understand the impact of the modifications on the performance of the GA. The flowchart of the GA is as shown in Figure 3.1. This test case is not related to the surface pressure estimation problems, but rather this prototype is used simply to illustrate the GA and its performance.

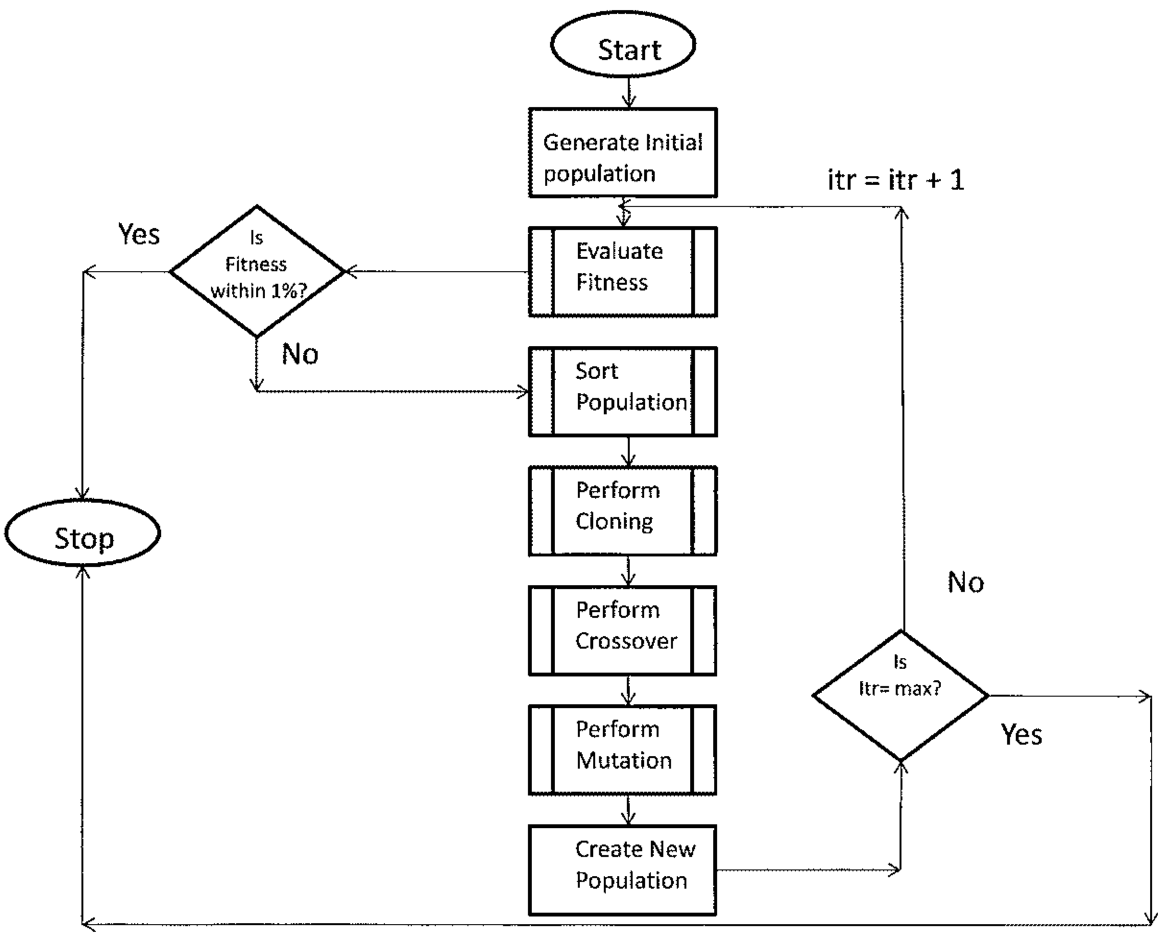

Figure 3.1 Flowchart of test GA.

3.1 Description of Model GA

To test the developed GA, the approach shown in Figure 2.1 will be used to find the best-fit third order polynomial for a function. The GA will attempt to find the set of coefficients—genes—for a polynomial to best represent an arbitrary function. For the test the genes of an individual are defined as the coefficients of the polynomial approximation to the function. An "arbitrary" function is used:

$$f(x) = 2-2.3x+1.2x^2+0.05x^3 \tag{3}$$

for the evaluation. The GA searches the space of possible genes—set of coefficients—and finds the best-fit individual for $0<x<1$. Of course it is expected that the GA will result in individuals that approach the individual with the coefficients

[2,-2.3,1.2,0.05],

which correspond with the test function. Before the GA starts execution, a population consisting of random individuals is generated. Each individual has four genes which are real numbers representing the coefficients of the polynomial. Once the population is generated, the fitness of each individual must be evaluated. The fitness function was defined as the normalized mean square difference between the polynomial and the truth function as shown in Equation 4.

$$\text{fitness} = 1-\sqrt{\frac{\sum \int_0^1 (\text{f(x)-truth})^2}{\sum \text{f(x)}^2}} \tag{4}$$

After the fitness of each individual in the population is calculated, the individuals are sorted according to their fitness values in ascending order. This ensures that the individual closest to the truth-value is at the top while the individual furthest from the truth is at the bottom. After generating and evaluating the initial randomly generated population, the GA begins execution. When the GA begins, the top half of the initial population is cloned, or selected, to propagate to the next generation. That is, the top 50% of the population survive to the next generation. The individuals that are furthest from the optimal solution are thereby eliminated.

After performing the cloning operation, the algorithm randomly selects two individuals, parents, to perform the crossover operation. One of the parents is chosen from the top 10% of the cloned population and the other parent from the rest of the population. This is done to ensure that the crossover is not performed on two individuals that are far away from the optimal solution. If the crossover is performed on two worst individuals, the algorithm may not converge or may take a very long time to converge because the new individuals created via mutation would also be far from the truth-value. The new individual, i.e. the child, created is then added to the population. After the crossover has been performed the algorithm randomly selects individuals to undergo mutation. The percentage of the population to undergo mutation is an input variable to the GA. In order to mutate a gene in the particular individual, a Gaussian random number is added to the gene. This Gaussian random number has a mean of zero and the standard deviation is the standard deviation of that gene in the population. So as the individuals in the population converge to the optimum solution, the standard deviation of that gene continues to decrease. Therefore, as the GA approaches the optimum solution the amount of mutation the gene undergoes decreases, allowing the GA to converge faster as the mutation operation significantly affects the execution time. The new individuals created by mutation are then added to the population and the population is again sorted in ascending order according to the fitness value. This process is repeated until the GA reaches an acceptable solution or until a certain number of iterations, whichever is earlier.

Various tests were performed on the model GA trying various combinations of crossovers and mutations to observe and analyze the impact of each on the performance on the GA. A large population of 80 individuals to perform the tests was considered.

3.2 Observations

By varying the percentage of individuals to be mutated, a set of different GA results was collected. The two factors observed during execution to measure the performance of the GA were the number iterations it takes to converge to a fitness value that is within 1% of the truth-value and how much better the fitness value is for the best individual in each generation.

3.2.1 No Mutation

The first case tested was of no mutation. As shown in Figure 3.2, the algorithm converges rapidly to a local optimum and finds it difficult to better the fitness for a very long period of time. This is called premature convergence. Lack of diversity in the population of the GA causes the GA to "converge" prematurely. This is because the GA at this point does not have the exploratory capability provided by the mutation operation and the population is only influenced by the crossover operation which only works with the available genetic information. One way of adding diversity to the population, other than mutation, is to introduce some random individuals in the population at each generation. Adding random individuals at each generation ensures the GA searches a large portion of the solution space, but also adds to the computational cost of the GA by increasing the execution time.

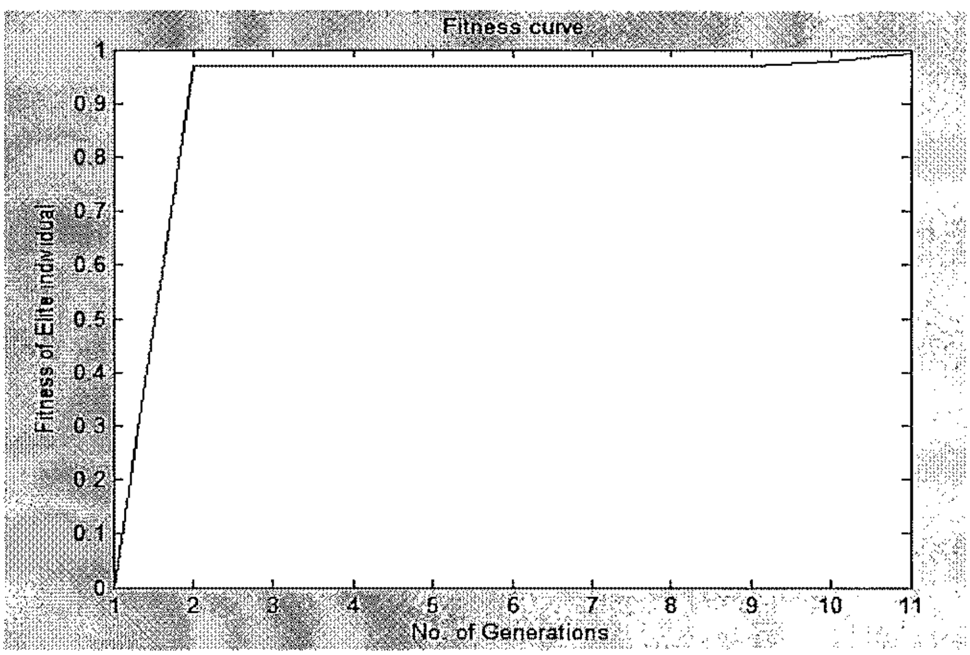

Figure 3.2 Convergence without mutation.

3.2.2 Varying the Percentage of Mutation

The most economical way of adding diversity to the population is by mutating the individuals in the population. The results of varying the percentage of mutation are provided in Figures 3.3 through 3.5. We can see that when 15%, 20% and 25% of the population is mutated, the fitness value of the best individual in each generation does not plateau for a long period of time indicating that the algorithm does not converge prematurely and the solution is more likely global in nature and a better fit to the truth function.

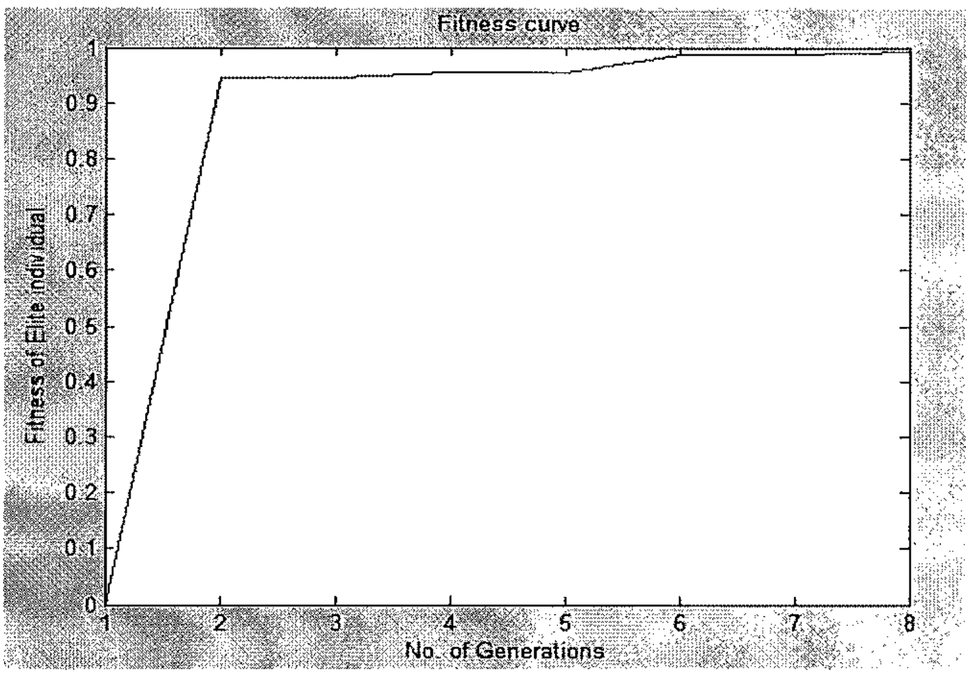

Figure 3.3 Convergence with 15 % mutation.

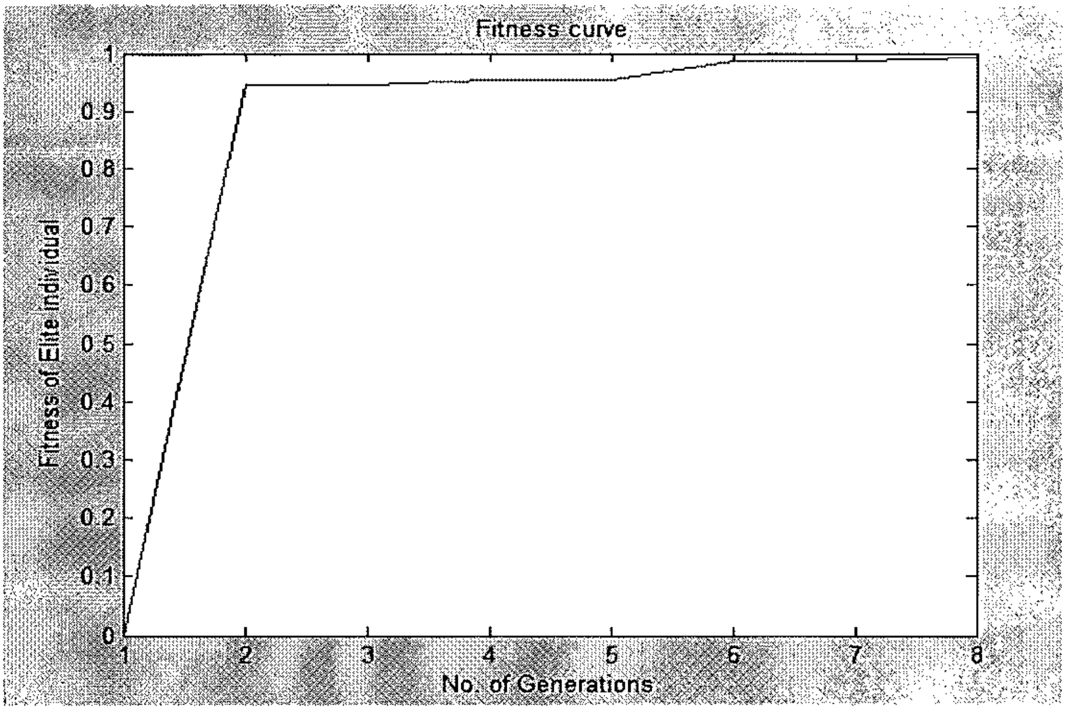

Figure 3.4 Convergence with 20 % mutation.

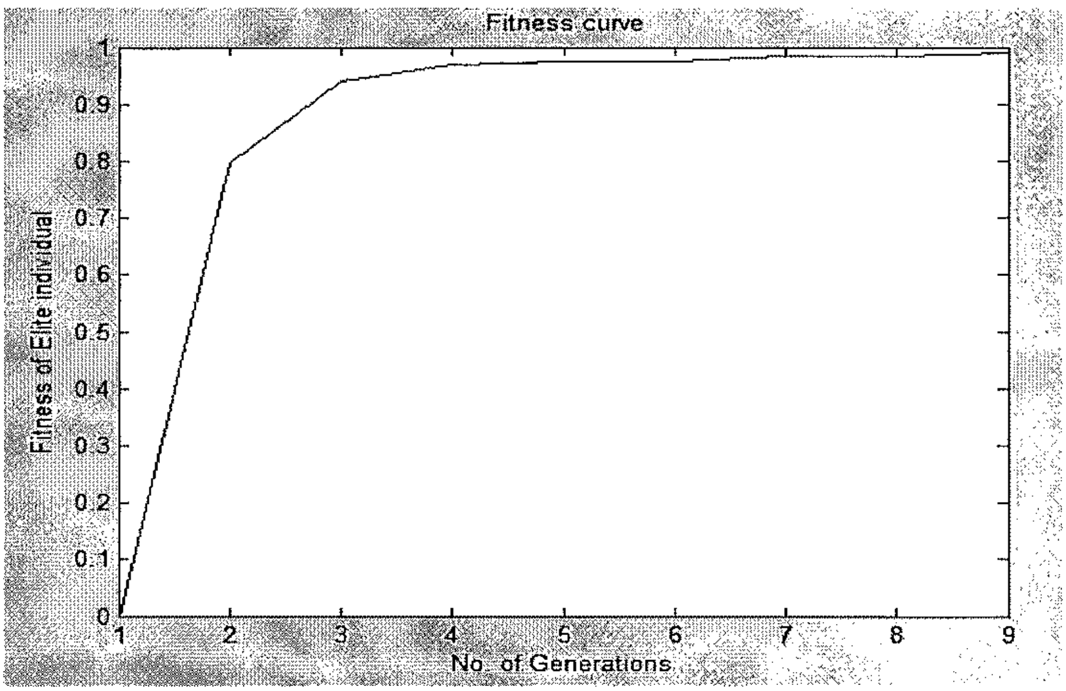

Figure 3.5 Convergence with 25 % mutation.

As the percentage of mutation is increased the quality of the solution for early generations is poorer, but the optimal solution gets better and the number of generations needed for convergence to 1 % is reduced. However, clones do not have to be reevaluated unless the truth-value changes but the GA must reevaluate individuals when mutated. Thus, there is a trade-off between the number of individuals that are mutated to get an acceptable solution in the fewest number of generations and the computational time required to complete a generation. This makes it very clear that mutation is very critical to the obtaining a global optimum quickly. The above tests indicate that the test GA is working and the effects of crossover and mutation are understood through the tests performed on the test GA.

CHAPTER 4
O_2 RADAR MODEL

4.1 Loss Model

Having studied the effects of mutation and crossover on the performance of the GA, the test GA was further modified to suit the final application for the computation of O_2 absorption. A model is needed to provide an estimate of the atmospheric loss for frequencies between 50-60 GHz. For this frequency range, only the absorption due to the water vapor and the O_2molecules is significant. While the absorption due to individual molecules can be calculated, the atmosphere includes many molecules and the interaction and collisions between these gas molecules results in a modification of the absorption, essentially broadening the absorption line. This substantially complicates the computation.

The approach that has been successfully applied in atmospheric remote sensing at microwave frequencies is to develop a line shape function to capture this broadening of the absorption line. These shape functions are typically a function of temperature and pressure, and model the effect of pressure broadening of the line [9]. By combining the attenuation for absorption lines in the frequency range of interest for water vapor and oxygen, the atmospheric absorption coefficient can be approximated [10][11][12][13] [14][15].

The coefficients in the loss models are typically empirically adjusted to fit experimental data. The approach used here to model the water vapor (V) and oxygen (O_2) absorption was developed by Liebe [16][18]. The absorption coefficient for V can be written [9] as:

$$\kappa_{H_2O}(f)=2f^2\rho_v\left(\frac{300}{T}\right)^{1.5}\gamma_l\left[\left(\frac{300}{T}\right)e^{-644/T}\left(\left(494.4-f^2\right)^2+4f^2\gamma_l^2\right)^{-1}+1.2\times10^6\right]\ \text{dB/km}$$

where the line width parameter γ_l is given as

$$\gamma_l=2.85\left(\frac{P}{1013}\right)\left(\frac{300}{T}\right)^{0.626}\left[1+0.18\left(\frac{\rho_v T}{P}\right)\right]\ \text{GHz}$$

f is the frequency in GHz, T is the temperature in Kelvin, P is pressure in mbar, and ρ_v is the water vapor density in gm^{-3}.

The microwave absorption spectrum of O_2 consists of a large number of absorption lines spread out over the 50-70 GHz frequency range. At the lower parts of the earth's atmosphere, pressure broadening causes the complex lines to blend together, forming a nearly continuous absorption band around 60 GHz. The traditional approach used for computing the absorption spectrum for 60 GHz has been to sum the absorption coefficients due to the individual lines using Van Vleck-Weisskopf line-shape factor [9]. According to the theory of collision broadening, the line width parameter γ of an isolated O_2 line should be proportional to partial pressure of O_2 [9]:-

$$\gamma=\gamma_0 P_{O_2}$$

where P_{O_2} is the partial pressure of O_2, and γ_0 is the line width at $P_{O_2}=1$ mbar.

To resolve this line width dependence on pressure, Rosenkranz applied the theory of bands composed of overlapping lines to the 60 GHz absorption spectrum and employed reasonable approximations to reduce the complexity of computation for practical use in remote sensing [9].

For an atmospheric O_2 concentration of 0.21 by volume, the O_2 absorption coefficient is given by

$$K_{O_2} = 1.61 \times 10^{-2} f^2 \left(\frac{P}{1013}\right)\left(\frac{300}{T}\right)^2 F' \ \text{dBkm}^{-1} \tag{5}$$

The function F' incorporates the line strength and determines the shape of the absorption spectrum. The resonant frequencies of the lines are distributed over the frequency range approximately between 50-70 GHz [9].

In addition to the oxygen and the water vapor, other atmospheric gasses and pollutants have absorption lines in the microwave spectrum [9]. Since their relative concentrations at sea level are very small, their contribution to the microwave spectrum is negligible in comparison to the contributions of the oxygen and the water-vapor. Therefore, the total gaseous absorption coefficient is given as

$$K_g(f) = K'_{H_2O}(f) + K_{O_2}(f) \ \text{dBkm}^{-1} \tag{6}$$

$$K'_{H_2O}(f) = K_{H_2O}(f) + \Delta K(f) \tag{7}$$

where $\Delta K(f)$ is a correction factor and $K_{O_2}(f)$ is derived from Equation 5.

Using the above procedure, the atmospheric absorption was modeled using Matlab and results for the top of the atmosphere were in agreement with results presented by Ulaby et al [9].

This loss model was used as the forward model to evaluate the fitness of individuals and forms the basis for the GA. The loss model is computationally very expensive and requires care when integrating it into the GA.

The GA developed to estimate the atmospheric pressure and track changes in the pressure is essentially the same as the test GA discussed earlier in Chapter 3, with some modifications to the mutation operation. Earlier, the standard deviation of the mutation operation was defined to be a function of a gene of the population. This can no longer be used as a parameter for mutation because the population changes with the change in pressure and the noise from the radar return. As a result, the standard deviation of the gene in the population is now strongly dependent on the SNR of the radar and changes in the scene viewed by the radar. Based on testing the standard deviation of the mutation operation is assigned to be a value less than 0.5.

The power of the reflected pulse received by the radar is a function of the absorption in the O_2 band. There is substantial attenuation in the received power of the radar due to the atmospheric absorption in the O_2 band. Depending on the SNR of the radar receiver, the radar estimate of the differential absorption will be noisy. For the expected SNR the standard deviation of the estimated differential loss may be quite large. As a result, the truth-value of the GA changes at each generation. While this increases the uncertainty in the pressure measurement, the impact on the GA may be more positive. The noise results in the radar estimate for the differential loss having a normal distribution with mean equal to the differential loss due to atmospheric absorption. This variation in the truth from generation to generation adds diversity to the population and should be evaluated as part of the GA algorithm.

The GA test case discussed in Chapter 3 used an initial population of 80 individuals. The initial implementation using 80 individuals in the population was far too slow to be useful once the computationally expensive forward model was added for atmospheric attenuation. Figure 4.1 shows the block diagram of the implementation of the GA along with the O_2 radar model.

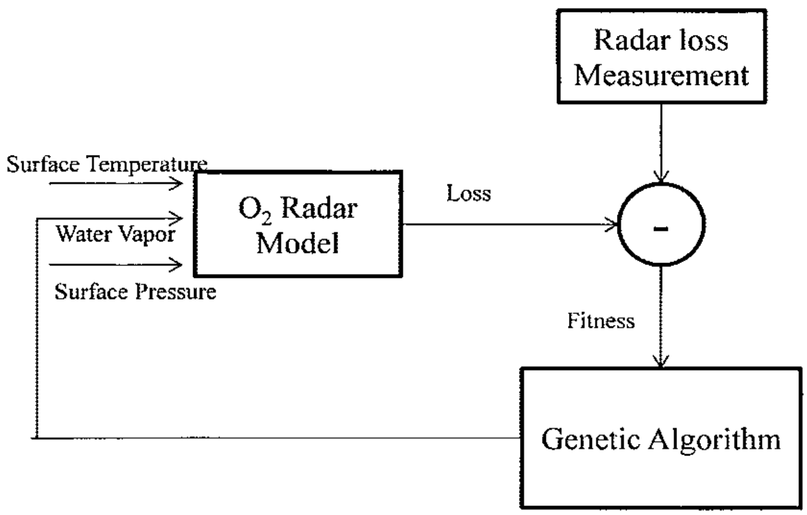

Figure 4.1 Block diagram of the implementation of GA with O_2 radar model.

We can see from Figure 4.1 that it is very expensive to reevaluate an individual because in order to do that we have run the computationally expensive O_2 radar model each time. Several approaches were explored to mitigate the computational expense of the atmospheric absorption model. A few methods were considered and developed to achieve the objective of this study.

4.2 Methods

4.2.1 Champion-Clan method

The Cluster Analysis approach discussed in Chapter 2 was modified to reduce the required use of the computationally expensive forward model. The cluster based on the fitness of the best individual in the cluster was evaluated rather than the average fitness of the cluster, thus only the best of the cluster, or champion, was evaluated using the fitness function. Instead of generating a population and then selecting the champions, the program begins with a very small number of champions then defined a clan (cluster) around each champion. At least 8 champions were experimentally determined to be required for the GA. These 8 individuals are considered as champions. The GA operations were then performed on these 8 individuals for 5 generations before creating a clan (cluster) around each of the 8 individuals. By doing this, the need to evaluate a large population at each generation is eliminated and thus reduces the execution time of the algorithm. It was observed during testing that the 8 champions would rapidly converge close to the optimal solution. The clusters around them did not significantly affect the convergence of the 8 champions. Further analysis revealed that in order for the clusters to have an impact on the convergence, a large number of individuals were needed in each cluster. Doing so almost negated the advantage gained by not evaluating the population for each generation. This approach, even with the addition of clans, was still faster and more accurate compared to the conventional approach. However, an attempt was made to reduce the need for clans to further improve the efficiency.

4.2.2 Minimum population approach

The clusters in the Clan-Champion Method did not significantly affect the performance of the GA and it could converge very quickly to the optimum solution with just 8 individuals in the population. Therefore, the decision was made to explore the use of a very small initial population size of 12 individuals for the GA approach. The genes of the individuals represent the operating frequency of the radar, the altitude, the water vapor in the atmosphere, the estimate of surface pressure and the number of layer the atmosphere is divided into. For each generation the best six individuals are cloned and survive to the next generation. In addition to these 'cloned' individuals the crossover and mutation operations described in the previous method are used to generate six additional "children".

As expected, reducing the number of individuals in the population greatly decreased the execution time of the GA. However, the convergence of the GA was only minimally impacted by the smaller population size. The minimum population method executed faster and quickly converged to an acceptable solution for a given true value of pressure. The performance of the minimum population approach was very encouraging for cases where the truth-value for pressure remained constant. However, when changes in the radar-measured attenuation were simulated, i.e. changing the truth-value, the performance of the GA rapidly degraded, and the number of generations required for convergence increased.

When the variance of the genes of the individuals was calculated as a function of generation number, it was determined that the variance, and so the genetic diversity, rapidly decreased in a few generations. This is likely the reason for the poor convergence for this GA for cases with changing truth-values. Since the population used is very small, after a few iterations there is not enough diversity in the population to force it to explore a wider solution space. When the truth value (pressure) changes the population lacks sufficient genetic diversity to follow the changing surface level pressure. The solution to this problem is to add diversity to the population.

Two ways to increase diversity were considered. One was to increase the standard deviation of the mutation operation and the other to add random individuals to the population at each generation. Both these approaches add to the computational cost. Increasing the standard deviation of the mutation function can adversely affect the GA's performance because if the GA is close to an acceptable solution, the high value of standard deviation may drive the GA away from the optimal solution for a particular generation and thus increase the time of convergence. The random individuals, though equally expensive computationally, would only come into play when the pressure value changed. Therefore, it was decided to add random individuals to the population to add diversity.

A model using the minimal population approach and the O_2 radar model was developed. This model simulates the radar return and uses the GA to find an optimal solution. It also has dynamic tracking capability to track the change in the pressure values. The flowchart of the model is shown in Figure 4.2.

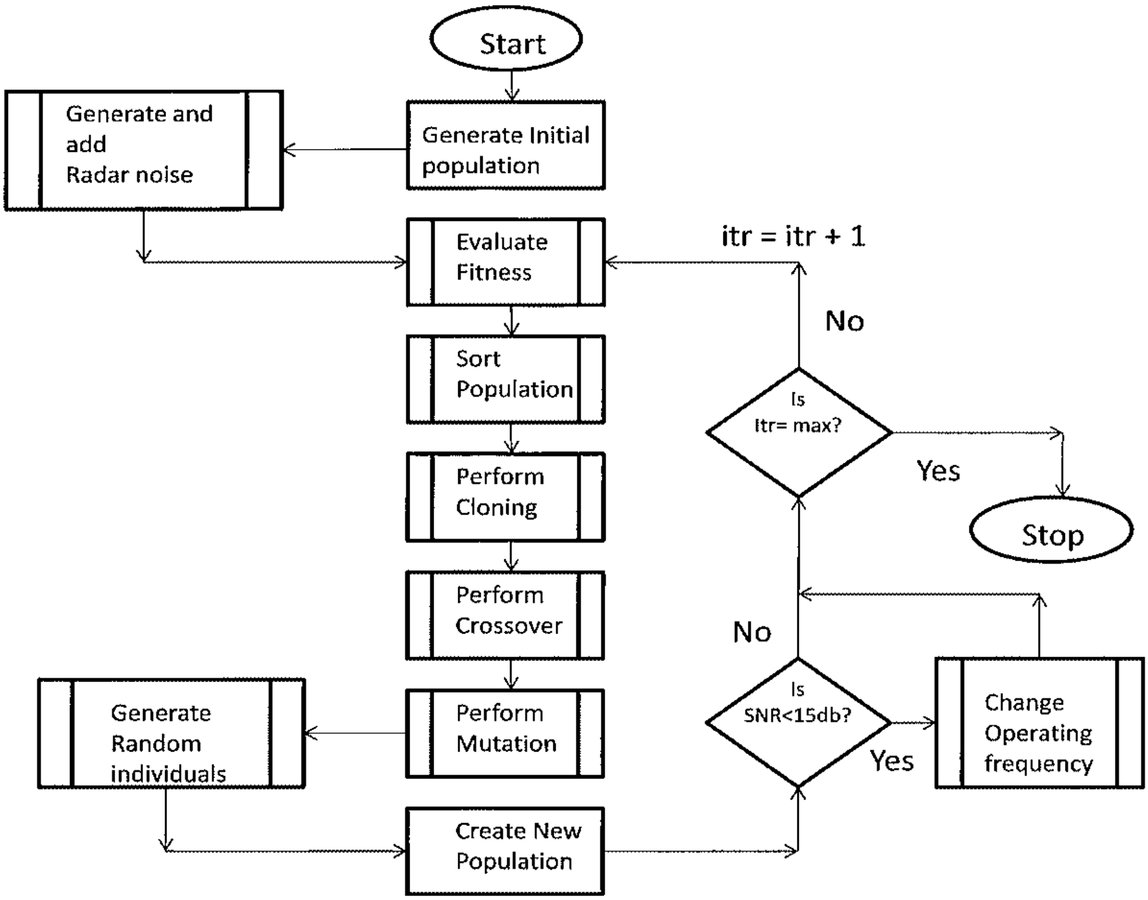

Figure 4.2 Flowchart minimal population with O_2 radar model.

When the GA starts execution, a random population is generated to initialize the algorithm. Then to simulate the noisy radar estimate for differential absorption, a Gaussian distributed noise is added to loss estimate to simulate radar SNR of 15 dB at 55 GHz and 1000mb. The noise variable is then added to the truth-value. This ensures that the truth is constantly changing depending on the noise variable at each generation. This method replicates the noise in the radar estimate of the differential loss. Once the noise is added to the truth-value, the fitness of the individuals in the population is evaluated. The GA then performs the sorting, cloning, crossover and mutation operations as discussed earlier in Chapter 3. The only change here is in the standard deviation for the mutation operation. The standard deviation in the mutation method is relatively lower than the model GA because the noisy radar return and the random individuals add to the diversity of the population which reduces the GA's dependence on the mutation operation to create diversity. After the mutation operation is performed, the GA adds random individuals to the population to increase diversity which is helpful in tracking the change in pressure values. The GA also manipulates the frequency of the radar in order to maintain a constant SNR around 15 dB. This is because at higher frequencies the precision of measurement is limited by the SNR. At lower frequencies the atmospheric attenuation is relatively low resulting in a high SNR. When the pressure changes, the atmospheric attenuation changes which affects the SNR. Since SNR is dependent on the atmospheric attenuation and frequency of operation, the frequency needs to be changed in real time to maintain an acceptable SNR.

The GA was tested with the initial population of 12 individuals to analyze its performance. The true value of the pressure is initially fixed at 1010 millibar (mbar). A test was then performed on how well the GA converges to that pressure with, and without, noise in the radar's attenuation measurement. Initially the frequency of the radar was fixed. The lower frequency is at 50 GHz and the upper frequency is at 53 GHz.

4.3Observation

Figure 4.3 shows that when there is no noise in the radar's loss measurement (infinite SNR), the GA very rapidly converges to the true pressure value and the rms deviation from the true value after 10 generation is then less than 1 mbar. Whereas, when noise is added to the measured attenuation to simulate radar SNR of 15 dB at 55 GHz, the GA still appears to converge within about 10 generations but the increased fluctuation in the retrieved pressure can be seen in Figure 4.3. Despite the noisy pressure values, the mean value for pressure for an experiment is relatively constant.

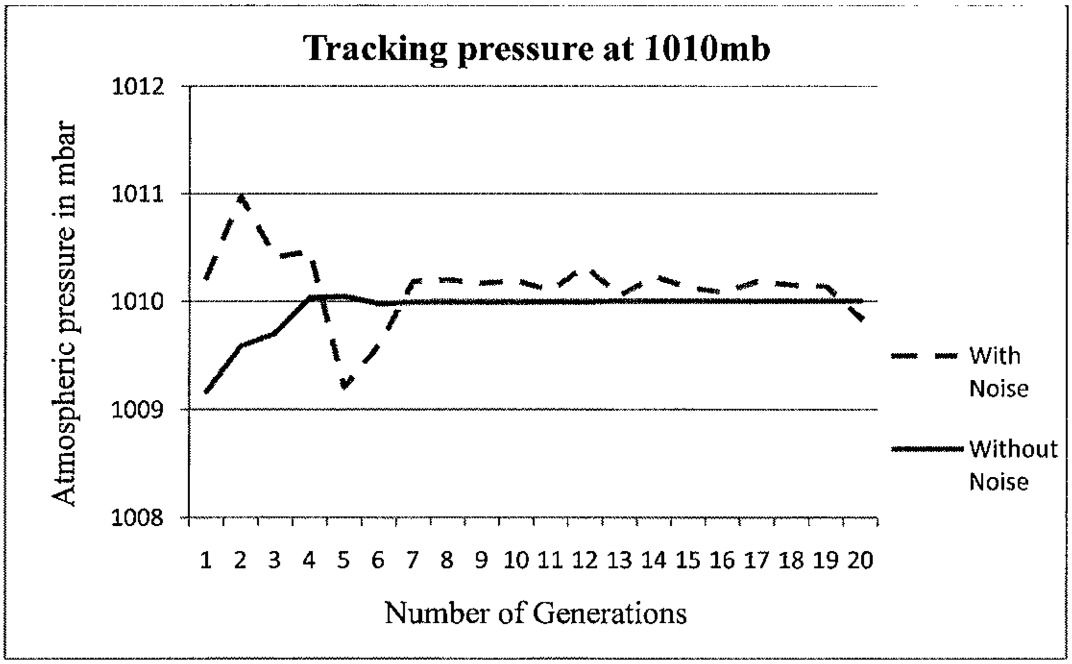

Figure 4.3 Tracking pressure at 1010 mbar.

Figure 4.4 shows the fitness of the best individual as a function of generation. When there is no noise the fitness of the best individual in the population rapidly converges to the fitness of the truth-value. As a result, the truth-value remains constant for the experiment. When noise is added, the fitness of the best individual in the population converges relatively slowly and keeps varying for each generation. This is because when noise is added the truth-value for each generation is different. As a result, the fitness value of the truth changes which in turn affects the fitness of the best individual.

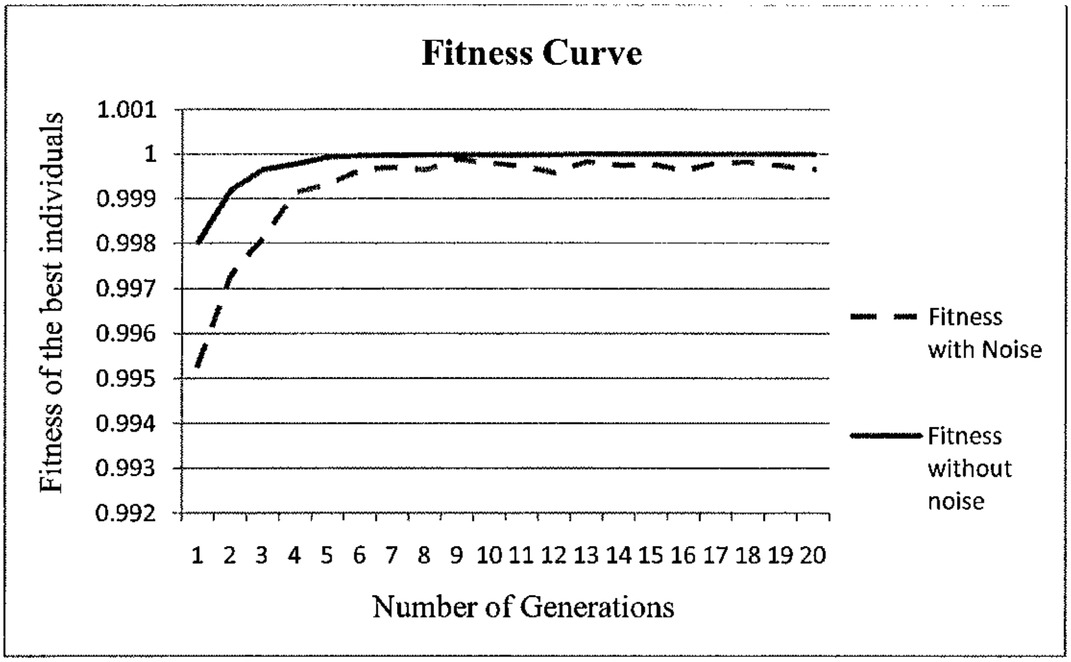

Figure 4.4 Fitness of the best individual at 1010 mbar.

The plot for variance of the best individuals (Figure 4.5) shows the variance among the best individuals at each generation over 25 experiments. The variance among the best individuals is more when there is noise and very low without noise. This plot again shows that it takes longer for the GA to converge to an acceptable solution when there is noise as opposed to when there is no noise. Again, the variance is due to the low SNR ratio of the radar.

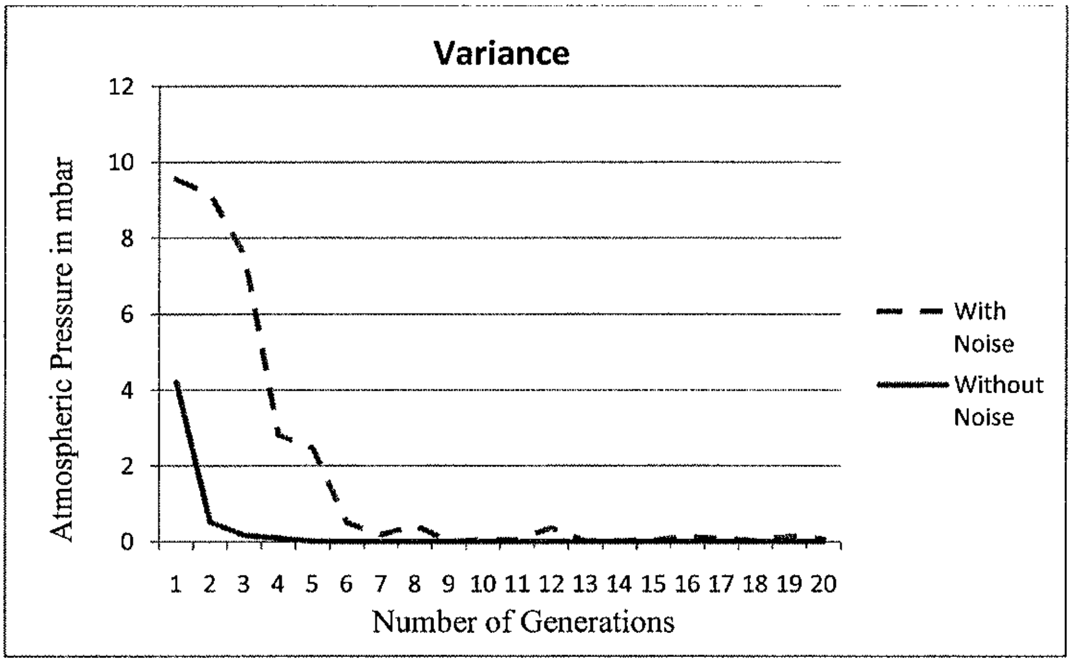

Figure 4.5 Variance of the best individual at 1010 mbar.

To ascertain that the GA works well at lower pressures the above test was repeated for a pressure value of 990 mbar The results of the experiment are shown in Figure 4.6. Here the pressure is very low, so there is less atmospheric absorption resulting in a very high SNR. Figures 4.3 and 4.6 illustrate that the GA works well in high as well as low pressure environments.

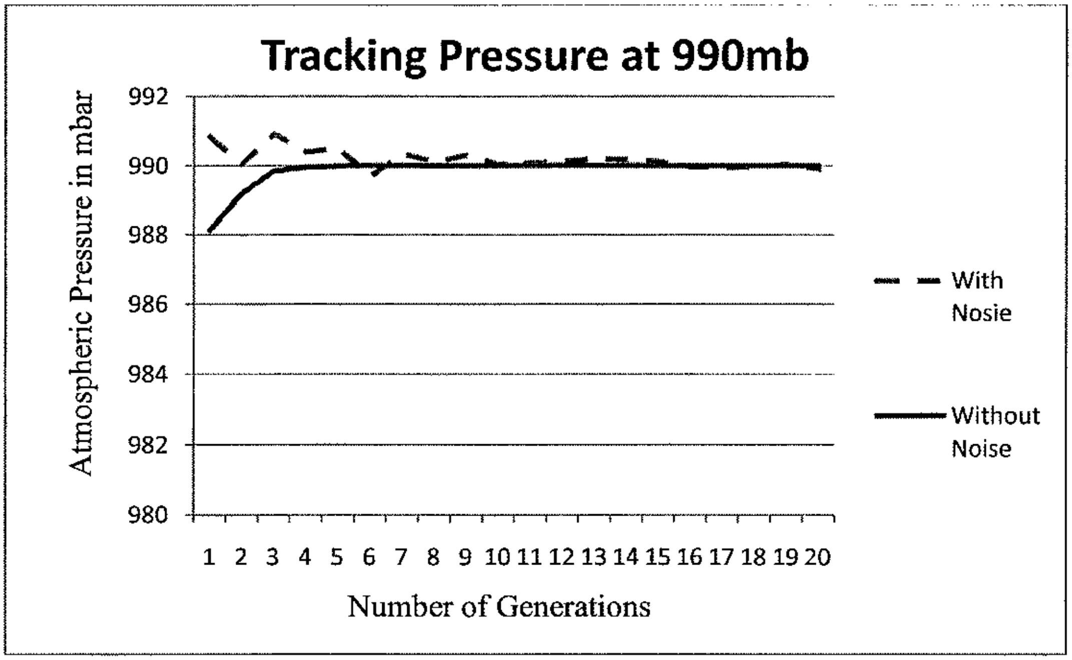

Figure 4.6 Estimating pressure at 990 mbar.

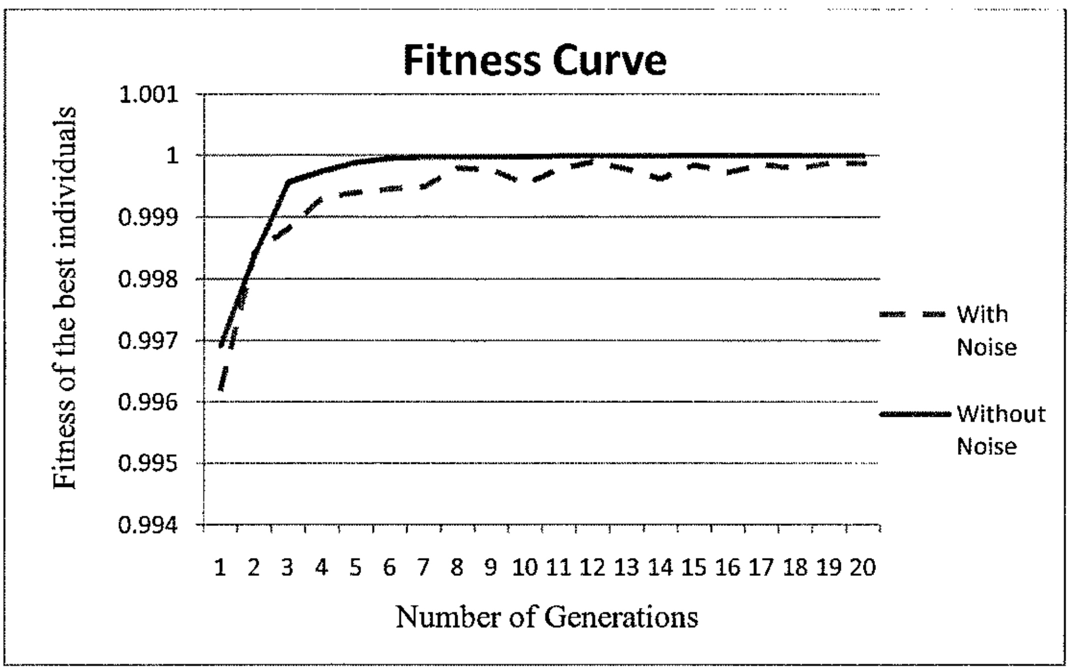

Figure 4.7 Fitness of the best individual at 990 mbar.

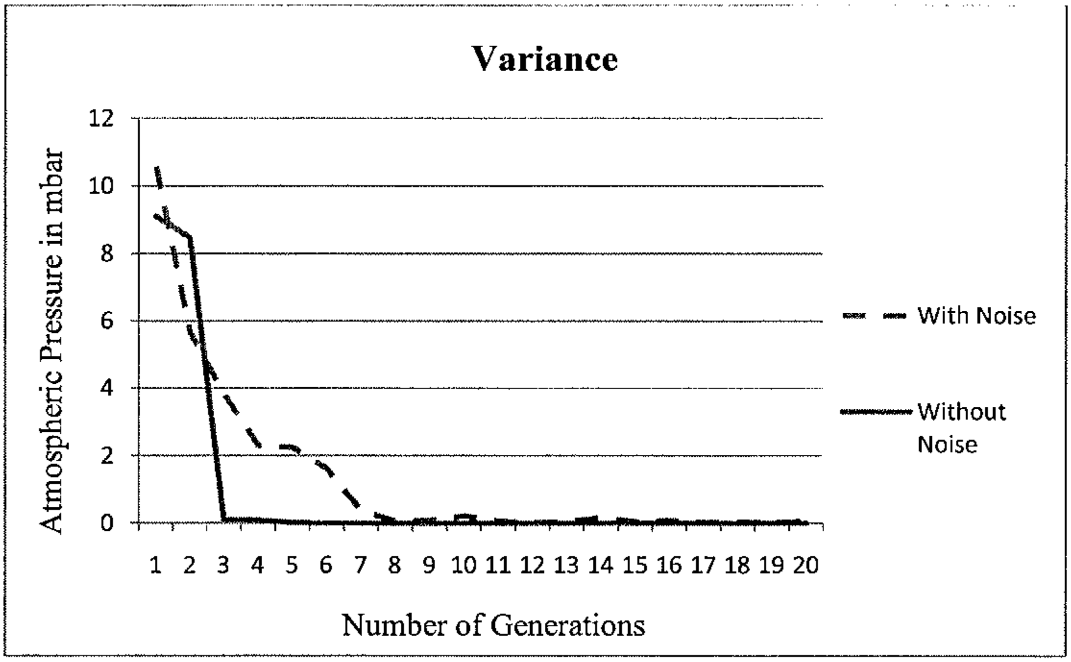

Figure 4.8 Variance of the best individual at 990 mbar.

From the above discussion, it is clear that when there is no noise in the radar return the GA seems to converge faster. One thing to be noted in the above discussion is that the pressure values are static and not changing. So for static pressure it is fair to assume that the maximum SNR will provide the best performance. In this study's application, the pressure values are changing. So, the GA not only needs to converge to an acceptable solution relatively quickly but also track the change in pressure. The SNR is affected by the frequency of operation of the radar and the atmospheric pressure. The higher the frequency of operation, the more loss due to absorption and at higher pressures there is more attenuation. Therefore, as the pressure changes the frequency of operation of the radar also needs to be changed to maintain a reasonable SNR to obtain useful results.

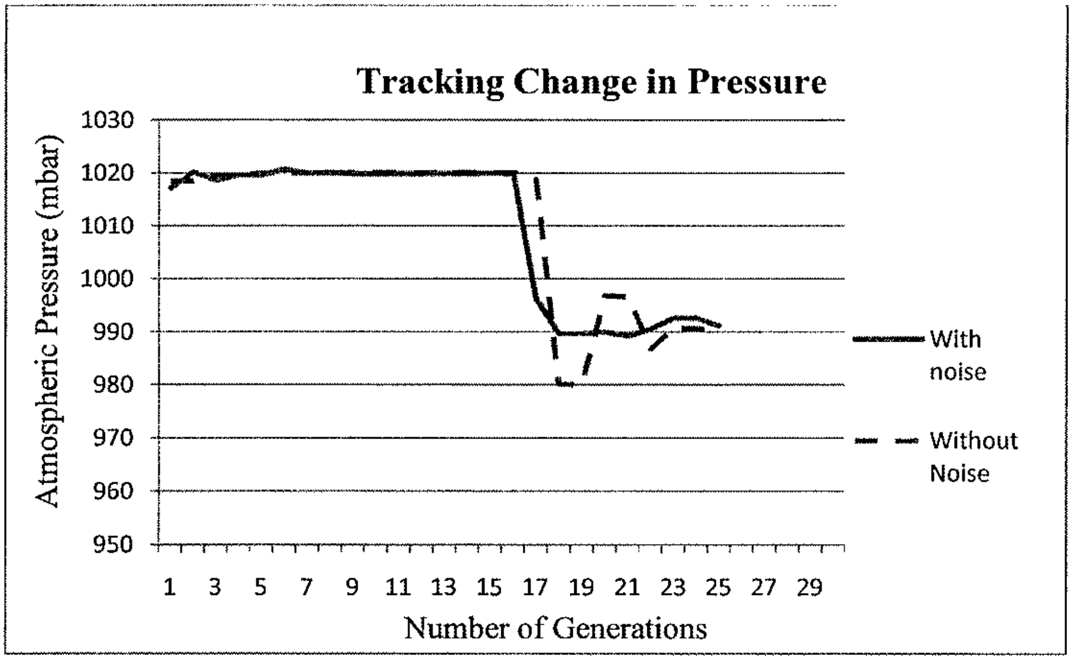

Figure 4.9 Tracking the change in pressure.

To simulate the performance of the approach for changing surface pressure, a simulation using a lower radar frequency of 50 GHz and upper frequency of 53 GHz, and allowing the surface level pressure to change from 1020 mbar to 990 mbar at generation 15 was performed. The radar SNR is set to 15 dB for 1000 mbar and 55 GHz, resulting in a very high SNR at the simulated measurement frequency of 53 GHz (approximately 35 dB). From Figure 4.9 it can be seen that when there is no noise, the GA converges very quickly to the optimum solution due to the infinite SNR. However, the no noise case has more difficultly tracking the change in pressure. From variance calculation of the pressure gene as a function of generation, there is very little diversity in the population after a few iterations. As a result, when the pressure changes, the GA is not able to track the change very well as it finds it difficult to break away from the current optimum value due to lack of diversity. It therefore has to rely on the random individuals in the population to drive it towards the new optimum.

When noise is added to the radar return, due to the high SNR at 53 GHz the GA still converges within 5 generations. More importantly the addition of the noise causes the truth-value for the GA to change for each generation. As a result, the GA is trying to converge to a new truth-value at each generation. This constant change due to the noise induces diversity in the population. The diversity generated in the population is large enough that when the pressure value changes from 1020 mbar to 990 mbar, the GA is able to track the change almost instantaneously. Such a large drop in pressure is very unlikely in the real world application except when there is a hurricane or a tornado like situation. The GA not only tracks large drop in pressure but also can track a change in pressure of about 1-2 mbar. The idea behind simulating the GA with such extreme pressure changes was to see how well the GA would behave in the most extreme situations. Hence, for this study's application it is desirable to have some amount of variance in the population to enable the GA to better track the change in pressure. More diversity can be added by having more mutation but that adds to the cost of computation. Thus, adding diversity to the population by using the inherent noise from the radar provides an approach that may enable the implementation the GA for surface pressure retrieval from the radar measurements and enable the GA to modify the radar frequency to optimize the measurement.

The variance of the pressure gene for each generation for various radar SNRs is shown in Figure 4.10. Figure 4.10 illustrates the rapid reduction in diversity after as few as 4 generations for 25 dB. As the SNR is reduced, to 15 dB, and then 10 dB the variance of the pressure gene remains finite and remains nearly constant after 10 generations. This may be very advantageous for this study's application. After the GA has converged to the correct truth value, or pressure, the noise inherent in the radar measurement of the loss may provide adequate diversity to enable the GA to track changes in pressure.

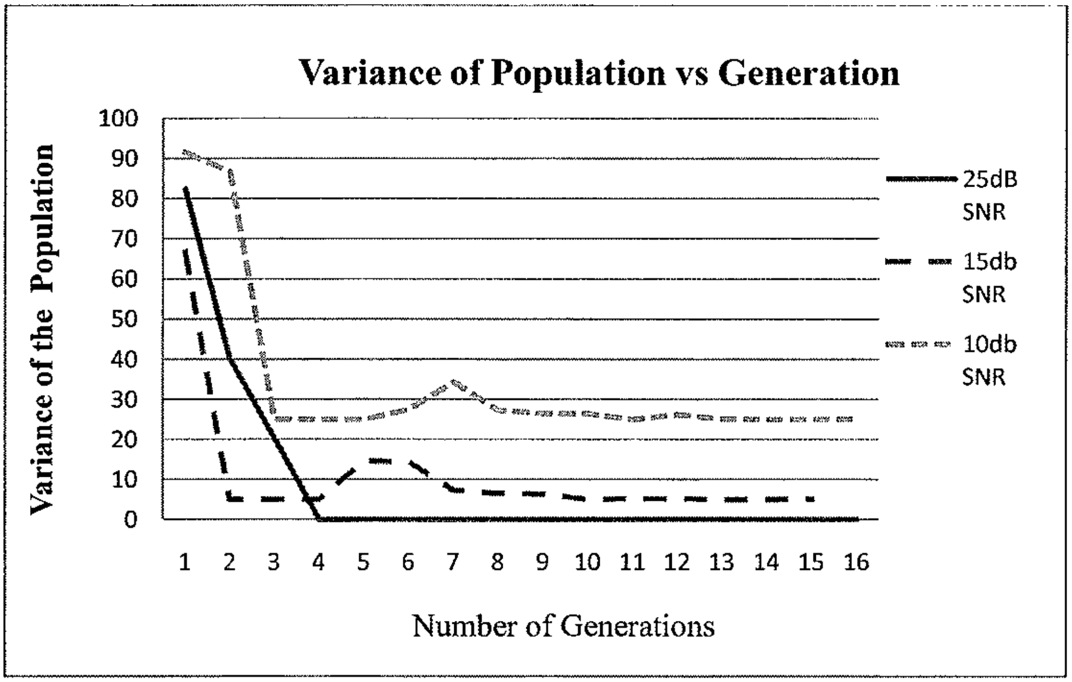

Figure 4.10 Variance of population at each generation.

The final simulation will demonstrate the frequency adjustment feature of the GA. As discussed earlier the SNR of the radar will be a function of the surface pressure (as well as other measurement parameters). Due to the rapid change in O_2 attenuation with frequency, the SNR is also a strong function of the radar frequency. The GA was designed to adjust the radar frequency to maintain a SNR of 15 dB to maintain genetic diversity and ensure the GA can track changes in the surface pressure.

The present implementation of the frequency adjustment feature estimates the SNR for 5 generations: if the SNR is less than 15 dB the radar frequency is reduced by 1 GHz. If the SNR is between 15 and 20 dB the radar frequency remains the same and if the SNR is greater than 20 dB the frequency is increased by 1 GHz. The actual optimum algorithm will, of course, be dependent on instrument details. However, the algorithm described in this thesis can be used to demonstrate the approach and the expected performance.

A simulation including the frequency adjustment algorithm where the initial radar frequencies are 50 and 52 GHz and the radar noise is set to correspond to a SNR of 15 dB for 55 GHz and a surface pressure of 1000 mbar, was also performed. The results of the simulation are shown in Figure 4.10. The surface pressure changes from 1020 mbar to 990 mbar at generation 15 and then changes to 960 mbar at generation 30. The results shown in Figure 4.10 demonstrate the ability of the GA to track changing pressures. In addition, the GA adjusted the upper radar frequency at generation 5, 10, and 15 and simultaneously modified the fitness function, or the forward atmospheric loss model. Since the genes describing an individual included pressure, and not loss, the fitness of an individual is not affected by frequency change and the GA correctly tracks the surface pressure through the frequency change.

Initially the SNR is very high resulting in very little variance in the population. At this point the population is very homogenous which makes tracking a change in pressure a little difficult. The GA takes some time before there is enough diversity to enable the GA to track the change in pressure. The subsequent changes in pressures are tracked better as the GA population has enough diversity. It can thus be concluded that the Minimal Population approach works successfully in tracking the change in pressure and quickly finding an optimal solution for the relative pressure value.

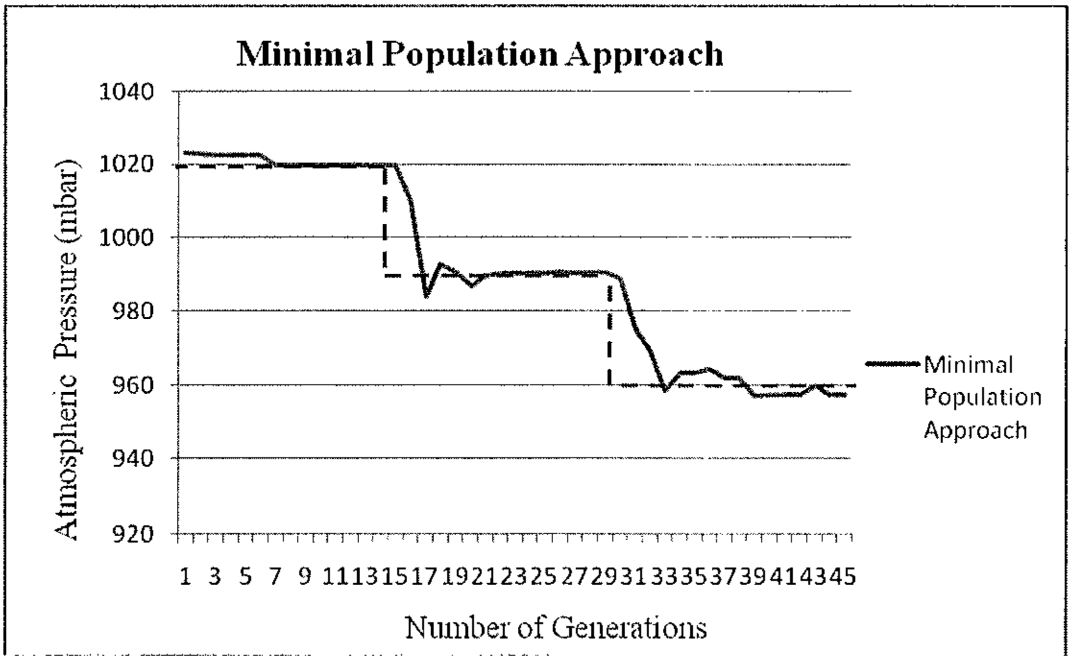

Figure 4.11 Tracking change in pressure using Minimal Population Approach.

CHAPTER 5

CONCLUSION

The genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. The GA is routinely used to generate useful solutions to optimization and search problems. A GA with dynamic tracking capabilities to estimate surface level pressure from radar measurements was developed in this research. The algorithms developed for the GA were design to converge quickly to an acceptable solution and track the changes in truth-values corresponding to the changing radar measurement.

The developed GA was implemented in Matlab and integrated with a microwave atmospheric absorption model to enable the simulation of the GA performance and demonstrate the concept of a GA radar processor. The GA techniques developed were designed to take advantage of the noise inherent in the radar measurement and to use very small population sizes. The processing required for the algorithm is relatively low due to very small population size and may be suitable for future real time radar processing applications. Future research could extend this concept and verify the performance using flight data as it becomes available

A new concept of using a very small population for the GA to facilitate faster convergence of the GA to the global optimum solution was developed in this research. While developing a real time processor was beyond the scope of this effort, it is believed the GA concept developed here is compatible with future real time processing approaches for the differential absorption radar. The developed algorithm could enable the use of differential absorption radar working at the 50-56 GHz O_2 absorption band to estimate the surface level pressure. This algorithm may have great potential for weather observations and other meteorological applications such as improve prediction of hurricane track and intensification which can help authorities to better plan evacuation during such an event.

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CURRICULUM VITA

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Research Publications:

1. Shah, Shivam, Roland Lawrence, Bing Lin, Steve Harrah, and Patricia Hunt. "Results of Flight Testing of a Differential Absorption Microwave Sensor for the Remote Sensing of Atmospheric Pressure." ***International Geoscience and Remote Sensing Symposium. 2010***, Honolulu, Hawaii, July 25-30, 2010.

Relevant_Coursework: Digital Systems Design and Techniques, Computer Architecture, Embedded Systems, Engineering Systems Modeling and Simulation, Advanced Digital Design, Microcontrollers and Microprocessors, Advanced Analog Circuits with Op-Amps, Computer Networks, Machine Learning, Digital Image Processing

Technical Skills:

Programming Language: C, C++, C#, VHDL, Verilog, Assembly Language, Visual C++, Shell Scripts

Microprocessors: PIC, Intel, ATMEL

Tools: Multisim, Matlab, Simulink, Eagle PCB, MPLAB IDE, Labview Visual Studio, MCC18 compiler, Aldec (AHDL), Visual Paradigm (UML)

Operating Systems: Windows 95/98/2000/XP/Vista.

Databases: SQL, MS-Access.

Web Technologies: HTML, XHTML, CSS, Java script, ASP