2011-01-01

Development Of A New Evolutionary Algorithm Based On Adaptive Echolocation Applied To A Multi Objective Version Of The Redundancy Allocation Problem

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DEVELOPMENT OF A NEW EVOLUTIONARY ALGORITHM BASED ON ADAPTIVE ECHOLOCATION APPLIED TO A MULTI OBJECTIVE VERSION OF THE REDUNDANCY ALLOCATION PROBLEM

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For my family and friends, for their love and support

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by

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THESIS

Presented to the Faculty of the Graduate School of
The University of Texas at El Paso
in Partial Fulfillment
of the Requirements
for the Degree of

MASTER OF SCIENCE

Department of Industrial Manufacturing and Systems Engineering
THE UNIVERSITY OF TEXAS AT EL PASO
December 2011

Acknowledgements

My life has been blessed with incredible people along this journey. Some of them I already knew, but others just got in it at the right time. I have learned so much from them and I just want to thank them and God for giving me the opportunity and the strength that I needed to not just initiate but keep going convinced that I was going to be able to complete this journey.

I am very grateful for having such an incredible mentor and advisor, without her wisdom and support I wouldn't be here, thank you so much to Dr. Heidi Taboada, who believed in me and gave me my first opportunity in the research field as an undergraduate student. Also I want to thank Dr. Jose Espiritu for his guidance and support and Dr. Rene Contreras for his assistance in every aspect of this journey.

My family is a vital part of my life I want to thank my dad and my mom, for their love and support throughout these years; they gave me the encouragement that I needed to keep going into this new quest. Also, to my brother that was always ready to help me and be by my side.

And last but certainly not least thanks for the love and the patience of all my friends that have contributed to this work in a direct or indirect manner. To my second family; my lab partners at the Ergonomics Safety and Productivity Lab that were always there to answer questions and to explain any doubts that I had.

Abstract

The intention of this research is to develop a new algorithm that it is mainly focus in the principle of echolocation or also called biosonar. This principle is active in many animals such as: birds, shrews, dolphins and bats, these last ones are going to be a fundamental part of our study. These animals use it as radar in order to find food, obstacles or just to locate objects. These animals use ultrasound beams with a certain degree of angle and multiple receivers; such as the two ears that are located slightly apart, so at the time of the returning echo the difference of loudness and also the difference between the arriving of one ear and the other tells them different and useful details about their prey or object in question. The main focus is going to be in the study of the bats in top of any other echolocating animal. The algorithm developed and explained in this paper uses the radar method in order to explore the search space in the looking of the optimal solution. The algorithm searches the solution space within an initial angle of 180 degrees. This is because the bat has a sight of no more than 180 degrees. After that the angle is going to be a changing parameter according to the new conditions of the problem. Also in between each solution there is a boundary that contains two solutions and is a simulation of the two ears of the animals, which are located slightly apart. This algorithm is applied to the well-known Redundancy Allocation Problem (RAP), investigating a single objective and multiple objective functions. The single objective will consider only reliability while the multiple objective function will simultaneously try to maximize reliability and minimize the cost and weight of the system.

Table of Contents

List of Tables

List of Figures

CHAPTER 1: Introduction

This thesis is focused in solving the Redundancy Allocation Problem (RAP) as a multi objective problem simultaneously optimizing the maximization of reliability, minimization of cost and minimization of weight of a system using a newly developed algorithm called a New Evolutionary Algorithm Based on Adaptive Echolocation. The Redundancy Allocation Problem is a well known problem that consists in improving the reliability of the system either subject to constraints or taking into consideration several objectives to be simultaneously optimized.

1.1 Redundancy Allocation Problem

The most important goal of a reliability design problem is to maximize the reliability of the system. The redundancy allocation problem (RAP) is also known as the reliability optimization problem where the system reliability is maximized, and the weight and cost of the system are to be minimized. The RAP is usually composed of multiple k-out-of-n redundant subsystems arranged in a series configuration. When we refer to a k-out-of-n configuration we are implying that there has to be k out of the n components operating to avoid system failure. As the name indicates a redundant system contains duplicates or backup components for multiple purposes. As Walker says “The implementation of redundancy can range from very elementary measures to relatively sophisticated ones”. As an example of a very basic redundant element we have the spare tire in our cars, or the extra copy as a backup of a very important document. But if we go to the other extreme of sophistication we can encounter the very complex computational systems working together in order to prevent catastrophically failures that can cost significant amounts of money. One of the main purposes of redundancy is to improve the reliability of a system and is heavily used in the areas where high levels of

reliability are needed such as spacecraft; however, its use normally involves additional cost, complexity and bulk [36] (Walker 2011). The System reliability can be enhanced with the utilization of redundant components but, then, conflicting parameters such as weight and cost appear and the problem translates from a single objective such as maximization of reliability into a multi objective problem where several objectives need to be optimized at the same time.

There are several approaches to solve this problem it can be solved as a single objective problem subject to constraints, or as a multi objective problem such as the case presented in this work.

Also there are two distinct ways to solve any of the mentioned cases, using mathematical or metaheuristic approaches. On one hand for the mathematical we can mention dynamic programming, integer programming or nonlinear programming models; the drawback is that these referred approaches are tedious procedures that some of the times because several objectives are involved do not give a feasible solution. While on the other hand among the most successful metaheuristic techniques we can quote Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Tabu search (TS), or Ant Colony Optimization (ACO) along with others.

1.2 Multi objective Optimization

The term multi objective optimization seems to be a very pompous term, but in reality for almost every problem that we encounter in real life we have several options that we need to take in consideration and evaluate at the same time because they are equally important, and there is no manner to just set them aside and forget about them. The problem is that these objectives are normally in conflict with each other. Let's put as an example the buying of a car. When someone is looking for a car the first things that jump into one's mind is the price, the

safety of the car, and the nowadays the mileage per every gallon of gas is very important. We can categorize these three things as our objectives to be optimized; we want a low price, a high safety rating for the car and also a high mileage per gallon of gas. But how we can decide on which objective is the most important of them all. We can't, that is why we take the three objectives and find the best possible combination that simultaneously optimizes all the objectives.

There are two distinct methods that solve these multi objective problems: mathematical approaches and metaheuristic algorithms. In the first approach the Multiobjective formulation is transformed and all the objectives are aggregated in just one complex objective but the problem here is that due to the fact of the joined objectives the solution given is most of the times not feasible.

While using metaheuristic approaches, the objectives are optimized simultaneously giving as a result a set of solutions that are said to be optimal according to the Pareto dominance concept. According to Zitzler and Thiele "These solutions are optimal in the wider sense that no other solutions in the search space are superior to them when all objectives are considered. And they are known as Pareto – optimal solutions" [40].

1.3 Thesis Objective

As it is said earlier the use of redundancy can be a very effective method of improving reliability nevertheless involves additional cost and complexity to the system studied. The Redundancy Allocation Problem can be found in many real life situations that include power systems, electronic systems, telecommunications systems and manufacturing production systems [27] (Ouzineb, Nourelfath and Gendeau 2008). According to the literature this problem has been extensively studied by a considerable amount of researchers. Each of them

proposes its own unique way to solve it using mathematical and metaheuristic techniques existent and available to the public.

Therefore, this thesis proposes a new algorithm developed to solve the RAP. The New Evolutionary Algorithm Based on Adaptive Echolocation applied to a multi objective version of the series parallel system, with multiple *k*-out-of-*n* redundant subsystems.

The objectives considered to be optimized simultaneously are the following:

- Maximization of Reliability
- Minimization of Cost
- Minimization of Weight

This thesis is divided into 6 sections and the remainder of this work is organized as follows: Chapter 2 discusses some basic concepts on single and multi objective formulation. Also presents several mathematical and metaheuristic methods found in the literature review used to solve multi objective problems.

Chapter 3 presents the Redundancy Allocation Problem in detail. There are several forms of the problem and the series parallel which is the one used is explained. The single and multi objective formulation are also described.

Chapter 4 presents the basic principles of echolocation, including the mimicking of the bats. Also the new developed algorithm, the model development and solution encoding. As well as the methodology step by step. Including the fitness functions used to evaluate the objective functions.

Chapter 5 presents the Illustrative Example for the RAP where the algorithm is applied and results are presented.

Lastly, chapter 6 presents conclusions and important aspects of the work that can be used for future research.

CHAPTER 2: Multi objective optimization methods

The idea of having more than two objectives to be optimized in an engineering problem is very common, not just in the engineering field, but in real life we have to deal with problems that engage in the simultaneous optimization of more than one objective. In order to make decisions we need to implement optimization techniques to solve these multi criteria problems. In the literature several techniques have been developed and presented to the public. In this section two different techniques will be explained: Mathematical and Metaheuristic techniques.

The mathematical methods basically use the technique of integrating every single objective function into just one big function to be optimized. In other words they transform a multiple objective problem into a single objective problem. The drawback of this technique is that some of the times or almost all of the times the solution obtained is not feasible.

On the other hand, we have the metaheuristic techniques; these methods have been growing in popularity lately and have been proven to obtain very good approximations to the optimal solution to the problem. These methods are applied to problems where the mathematical methods cannot be implemented. On the opposite side of the mathematical methods the metaheuristic techniques applied to multiple objective problems give a set of solutions, these solutions obtained are called Pareto set of solutions, and are nondominated solutions. These nondominated solutions are based on the concept of Pareto optimality [40] (Zitzler and Thiele 1999). This concept states that in order for a solution to be considered nondominated each of the objective functions have to be better than any other solution. Figure 1 illustrates this concept.

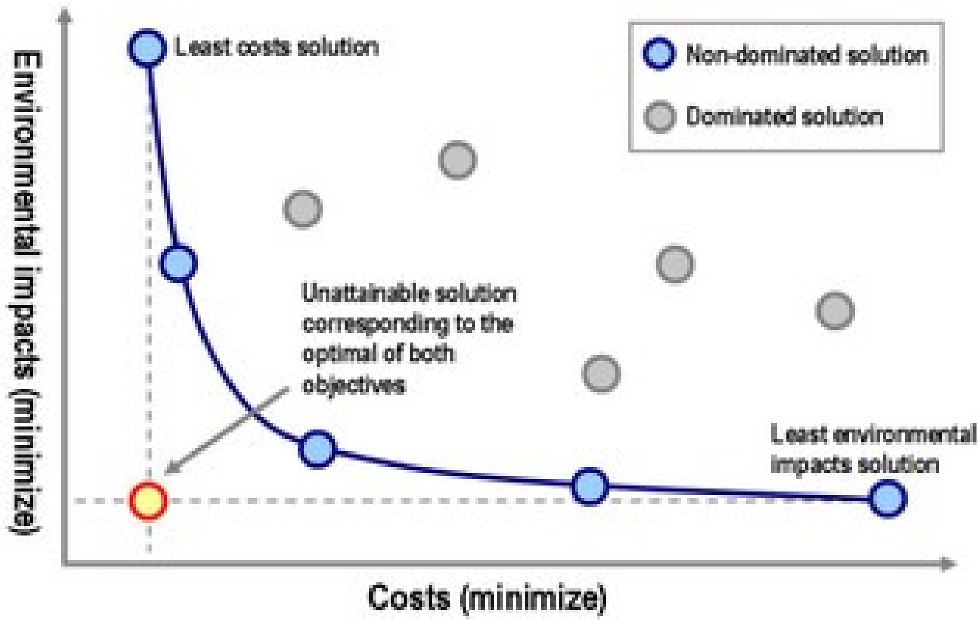

Figure 1: Pareto optimality

The following model presented by Equation 1 is the model for a multiple objective optimization problem.

$$Min\ , Max\ \left(f1(x), f2(x), .., fn(x)\right) \tag{1}$$

$$x \,\epsilon\, D \ \subseteq X$$

$$subject\ to\ k\ constraints$$
$$hi(x) \ \leq\ 0 \quad (inequality\ constraints) \quad i\ =\ r+1, .., k$$
$$gi(x) =\ 0 \quad (equality\ constraints) \qquad i\ =\ 1, .., r$$

Where:

$n \geq 2$ number of objectives

D feasible region of solutions

X *decision variable space*

Where, $(f1(x), f2(x), .., fn(x))$ are the objective functions to be optimized and habitually are in conflict.

2.1 Mathematical Models

In the past, numerous approaches have been developed by many authors to solve the RAP. Some of the mathematical techniques used to solve the RAP include:

- The Weighted Sum Method,
- Goal Programming,
- Lexicographic Method,
- Utility Theory

In the next sections we will discuss each of the above mentioned methods in deep.

2.1.1 The Weighted Sum Method

From the mathematical methods the most widely used method for multiobjective optimization is the weighted sum method [19] (Kim and de Weck 2006). This method converts each single objective into an aggregated objective function by multiplying each objective function by a weighting factor and summing up all individual weighted objective functions. With this procedure we obtain a new unique objective function that it is going to be the new objective function to be solved. The decision maker decides on the weights that are going to be assigned. Equation 2 is a representation of the weighted sum model:

$$J_{\text{weighted sum}} = w_1 J_1 + w_2 J_2 + \cdots + w_m J_m \qquad (2)$$

Where:

w_i (i = 1, · · · ,m) is the weight assigned to each individual objective.

The goal here is to transform the problem in to a single objective optimization problem [9]. According to some research done by Messac and Mattson (2002) Das and Dennis (19997) and Koski (1985) there are two main drawbacks to this method [19]:

- Generally, the solutions are not uniformly distributed.
- The weighted sum method cannot find solutions that lie in the nonconvex regions of the Pareto front; even though increasing the number of steps of the weighting factor has been tried that, does not resolve this problem.

2.1.2 Goal Programming Method

The main idea of the Goal Programming method (GP) relies on the concept of satisfying of objectives [33] This GP approach was first exposed by (Charnes, Cooper and Ferguson 1955) [5]. In GP aspiration levels are assigned for each objective by the decision maker, then the deviations from these aspiration levels are the ones to be minimized.

The general model for the GP is presented in Equation 3:

$$Z = (\, w_1|f(x_1) - \, g_1|) + (w_2|f(x_2) - g_2|) + \cdots + (w_n|f(x_n) - \, g_n|) \tag{3}$$

Where:

Wn is a non negative constant that represents the relative weight assigned to the deviation variables,|$f(x_n)$- g_n| represents the deviation variables.

In GP a multi objective optimization problem is converted in to a single objective problem seeking to minimize the *Z* function. A drawback of this method is that solutions hidden in concavities can fail to be discovered [9].

2.1.3 Lexicographic Methods

The basic principle of the Lexicographic optimization establishes a hierarchical order among all the optimization objectives [28]. As well as in the other mathematical models already explained the decision maker assigns the importance to the objectives. Moreover, the objective functions are arranged from the most important to the least important; giving them a hierarchy level that defines an order. As it is said in the literature the most important objective is infinitely more important than a less important objective. This step by step process first optimizes the first and most important objective already ranked by the decision maker, $f_1(x), f_2(x), \ldots, f_n(x)$ without taking into consideration the other objectives [1]. A representation of this type of method is given in equation number 4.

$$\min f_1\,(x) \tag{4}$$

$$s.t.\, x \in X$$

Then, this objective function is added as another constraint for the next objective function based on the value found in the previous step. The experimentation is continued until the final objective considered is reached.

2.1.4 Utility Theory

This multicriteria decision-making technique also known as utility function or value function is based on the following hypothesis: in any decision problem, there exists a real valued function *U* defined on *A* which the decision maker wishes to maximize [29]. The main disadvantage is that, in order to use this method we need to know the value function, and in

some cases is really difficult to determine it. The utility function has its basis in the relative "liking" of an evaluator with respect to the outcome. According to (Georgy, Chang and Zhang 2005) [15] a mathematical function between all possible outcomes of each individual measure and their corresponding relative liking to the evaluator could be developed. This mathematical function is the utility function. A general formulation can be viewed in equation 5.

$$\text{Maximize } v\,(f(x)) \qquad (5)$$

$$s.t.\, x \in X$$

2.2 Metaheuristic Models

As Colette and Siarry say in their book Multiobjective optimization "Metaheuristics are general optimization methods dedicated to hard optimization problem. These methods are, in general presented as a concept." Basically these Multiobjective techniques are developed from theories like natural selection, survival of the fittest and concepts such as echolocation. Also, they are based in natural behaviors of animals such as the swarms, human mechanisms like the neural networks, and Mechanical procedures such as Simulated Annealing.

Some of the well-known algorithms that will be explained later on in this thesis are:

- Tabu Search
- Simulated Annealing
- Genetic Algorithms
- Ant Colony

These are some of the most significant metaheuristic techniques found in the literature.

2.2.1 Tabu Search

Tabu Search (TS) is a technique that was originally proposed by (Glover 1977) [16] as one optimization tool applicable to nonlinear covering problems [3]. The main characteristic is the iterative process that follows in order to get to a local or global optima of the problem being solved .This technique has been implemented successfully into a number of combinatorial optimization problems such as production scheduling (Brandimarte 1992) [4], Redundancy allocation problem (Ouzineb, Nourelfath and Gendeau 2008) [27].An obvious strategy for the algorithm to escape from local optima is to drop the condition that a move is only performed if it leads to an improvement (Michiels, Aarts and Korst 2007) [25].This strategy guides in to a continuous improvement of the objective function, but the drawback is that sometimes it can revisit a same local optima that we already set aside. In order to prevent this behavior TS, has a so called Tabu List. This list keeps track of the recently evaluated solutions in order to prevent the reappearance of them and reevaluation of a solution that was already visited.

A tabu list can be considered as a short term memory of tabu search [25]. The length of this tabu list can be as short or long as the person applying the algorithm wants. The shorter the list the more cycling can occur, this means that the algorithm can revisit a specific solution over and over again. On the other hand the larger the list the more restrictions on the neighborhoods exist and also the computational time increases.

In figure 2 a representation of the pseudo code of TS is shown. And in figure 3 a flowchart of a generic tabu search is shown.

algorithm Tabu search

begin
  $T := [\,]$;
  $s :=$ some initial solution;
  $s_{\text{best}} := s$;
  repeat
    find the best *admissible* $s' \in N(s)$;
    if $f(s') < f(s_{\text{best}})$ **then** $s_{\text{best}} := s'$;
    $s := s'$;
    update tabu list T;
  until stopcriterion;
end;

Figure 2: Pseudo-Code for Tabu Search

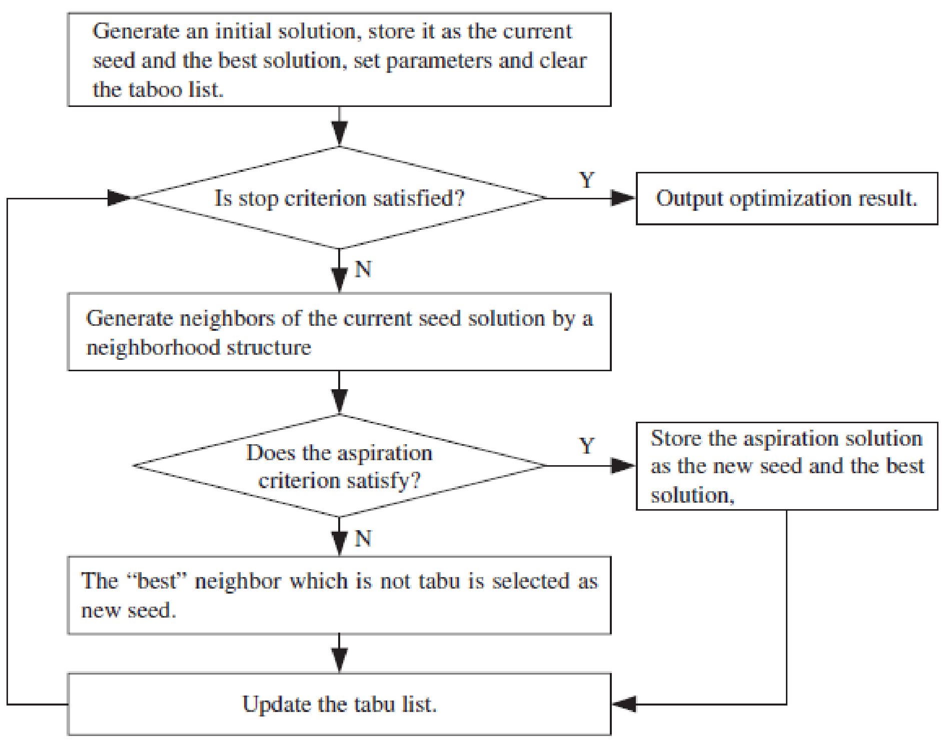

Figure 3: Generic Flowchart

2.2.2 Simulated Annealing

Simulated Annealing (SA) was proposed by (Metropolis, et al. 1953) [24]. The main idea of SA is the analogy between the objective function to be minimized and the energy of the states of the solid [13]. The term annealing by itself means the rising in temperature of a solid until it reaches its melting point than cooling of the material until it reaches the desire characteristics, all of this needs to be done carefully in order to attempt the desire states of the solid. These different states that the solid can reach correspond to the different feasible solutions of the problem being optimized, and the energy of the system corresponds to the function to be minimized.

According to Johnson et al. (1987) and Eglese (1990), there are some precedents that need to be followed in order to implement the SA to any combinatorial optimization problem. These precedents are divided into two categories:

- Problem Specific choices, and
- Generic Choices

For the first category, the problem needs to be clearly formulated in order for the set of solutions to be defined; also the neighborhood of any solution must be defined. And as in any other metaheuristic we need to generate a random solution first.

For the second category, as the name indicates are more formal decisions or also called parameters needed to run the algorithm. These parameters are:

- The initial value of the temperature parameter T.
- A temperature function T (t) determines how the temperature is going to be changed.
- The number of iterations N (t) to be performed at each temperature.
- A stopping criterion to terminate the algorithm.

Simulated Annealing is a simple algorithm that performs local searches and in order to keep away from becoming trapped in a local optimum point the algorithm starts with a relatively high temperature T, while the temperature gradually drops the algorithm starts attempting several moves at each different level of temperature [13].

Figure 4 shows the pseudo-code for SA, and Figure 5 shows the flowchart for SA.

```
Simulated Annealing algorithm in pseudo-code
-----------------------------------------------------
Select an initial state i ∈ S;
Select an initial temperature T > 0;
Set temperature change counter t = 0;
Repeat
Set repetition counter n = 0;
  Repeat
  Generate state j, a neighbour of i;
  Calculate δ = f(j) − f(i);
  If δ < 0 then i := j
     else if random(0, 1) < exp(− δ/T) then i := j;
  n := n + 1;
  until n = N(t);
t := t + 1;
T := T(t);
until stopping criterion true.
```

Figure 4: Pseudo-code SA

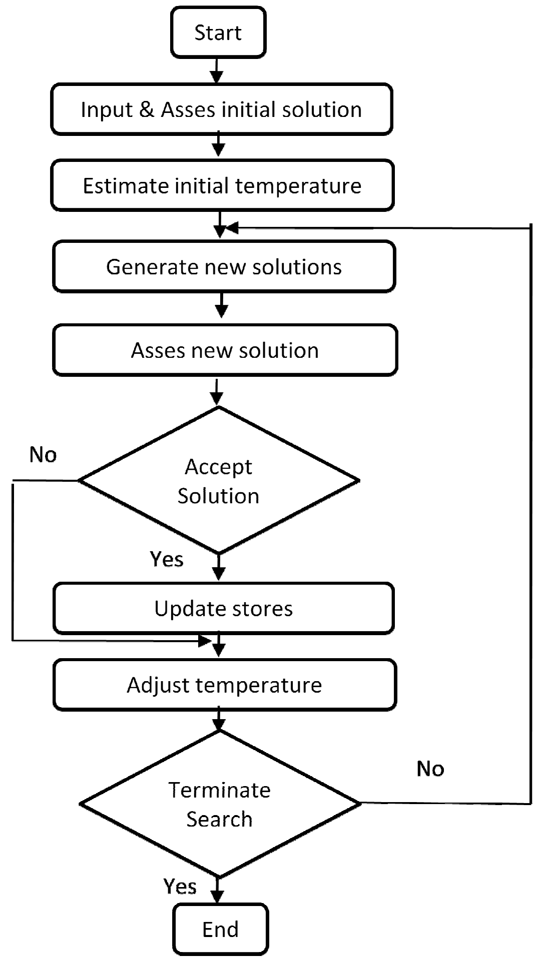

Figure 5: Flowchart SA

2.2.3 Genetic Algorithms

Genetic Algorithms are part of the Evolutionary Algorithms and as the name indicates they evolve in order to find Pareto optimal solutions. Primarily GA's are inspired by Darwin's theory of biological evolution and natural selection. This algorithm adopts to its main steps and parameters some genetic terminology such as:

- Chromosome – genetic material contained in a string, in this case is possible solution for the problem containing valuable information.
- Inheritance – passing good or bad genes to the offspring.
- Mutation – inserting or replacing one or several genes in to the chromosome

- Crossover – the mixing of the parents chromosomes to create new population
- Selection – the selection of the best chromosomes.

1. The first step is to initialize the population and this is almost always done randomly, the size of the population is specified by the nature of the problem [39]. Once the population has been randomly generated the algorithm evolves using the already mentioned genetic operators.
2. The next step after the creation of population is the evaluation of fitness for every solution. The purpose is to have a Pareto set with non-dominated solutions. To perform this evaluation a fitness function needs to be selected.
3. Once the Pareto set has been established the reproduction stage is the next step, and it involves the crossover, selection and mutation operators.

   3.1 The crossover operator represents the mating of the individuals. Two individuals (parents) are chosen from the population using the selection operator, and then a crossover method is chosen to attain the goal of producing offspring. In here the purpose is to create a new and better generation of population than the one before. The main concept behind the improvement of a crossover operator is trying to distinguish between bad genes and good genes [14].One of the most common operators used are the one-point or multiple point crossover. An example of one- point and multiple point crossovers are shown in figure 6, and 7.

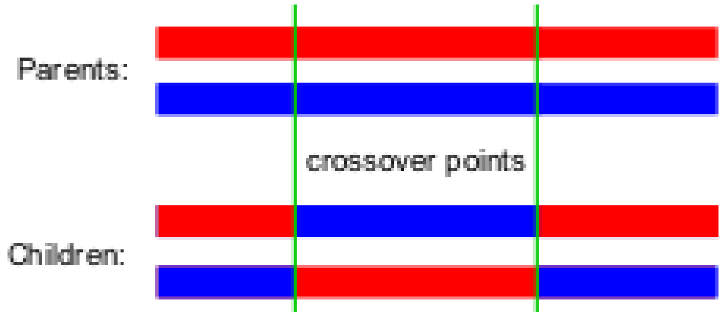

Figure 6: One- point Crossover

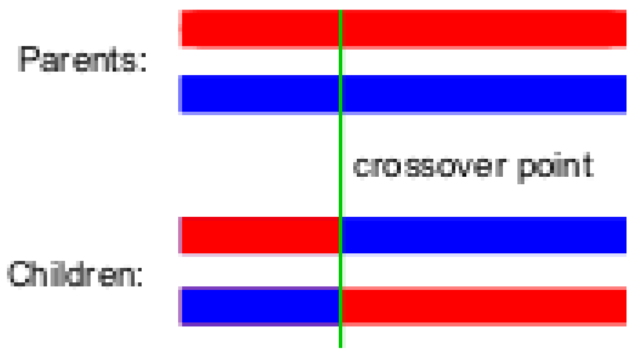

Figure 7: Multiple point Crossover

3.2 Once the crossover has been performed and the new population has been created, mutation is introduced, the main reason is to give and maintain diversity in the new population. The probability of mutation is very low because we just want to introduce a little of variation. An example of a variety of mutation is a two type mutation; this mutation chooses two different points in the chromosome randomly and exchanges them by two other random genes. Figure 8 shows this type of mutation.

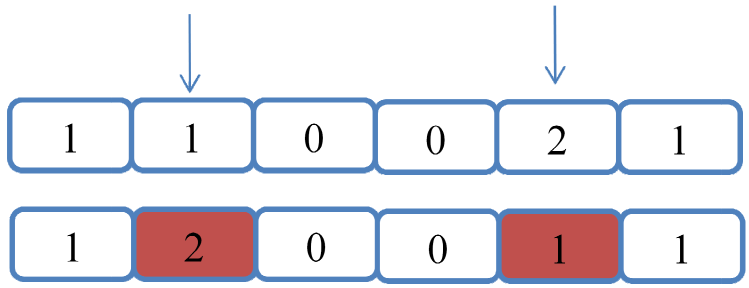

Figure 8: Two point mutation

4. The next step, is to go back to step number two and perform the analysis of fitness, once is done the new pareto will be available to follow with the reproduction process, and start and iterative process until the termination criteria is reached.

   Figure 9 Shows a Flowchart of the GA's methodology.

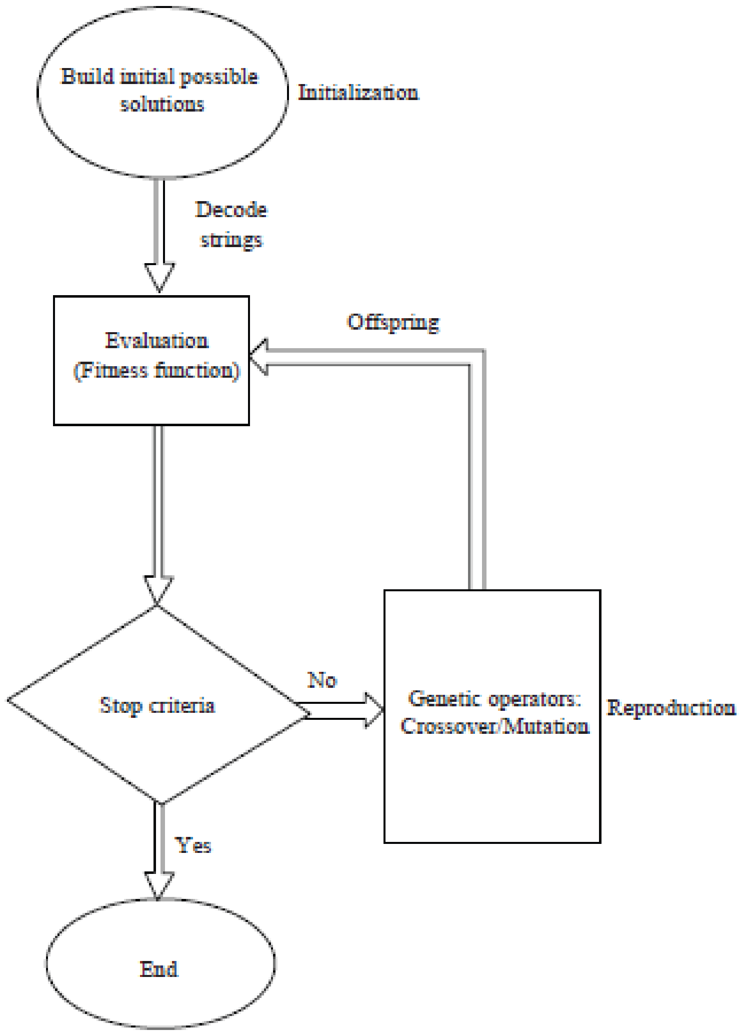

Figure 9: GA Flowchart

2.2.4 Ant Colony Optimization (ACO)

As well as particle swarm Ant Colony Optimization is inspired in the behavior of a specific animal in this case the ants. This analogy with nature in specific ethology permits the comprehension of natural principles such as the finding of food, and helps in the optimization of human- made problems. ACO is one of the adaptive meta-heuristic optimization methods inspired by nature which includes simulated annealing, GA, and tabu search [23].

ACO simulates how the ants find the shortest path from a specific point as an example their nest up to a second point that can be the source of food. It involves certain parameters such as the pheromone density, the evaporation of the same, and the ant. The main characteristic of ACO is that each generation has a new and different set of solutions while other metaheuristics focus in just improving their already attained solutions. The ACO was originally inspired by the Ant System proposed by Dorigo et al. [11]. Since the ants walk through a feasible space in order to find their food and to return to their nest, we can view it as a graph were at the end we are going to find the shortest path from the starting to the end point a representation of this is in figure 10.

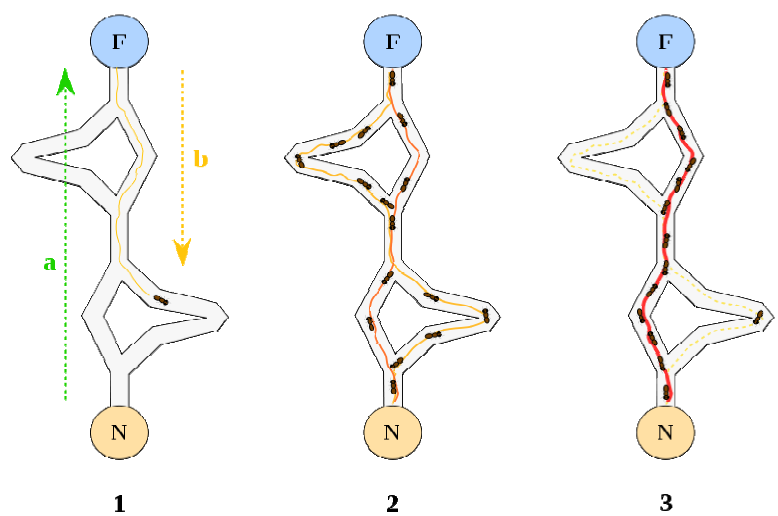

Figure 10: Finding the shortest path

The basic methodology of this algorithm is shown in figure11.

Algorithm 1 The Ant Colony Optimization Metaheuristic

```
Set parameters, initialize pheromone trails
while termination condition not met do
    ConstructAntSolutions
    ApplyLocalSearch (optional)
    UpdatePheromones
endwhile
```

Figure 11: ACO methodology

According to Dorigo et al. (2006) [12] there are three main phases on this metaheuristic technique. These three phases will be iterating and at the same time are going to construct a set of solutions. Each solution will be new for each of the iterations.

- First phase: *Construct Ant Solutions*: This building of solutions process is like walking on a graph. A set of *m* artificial ants builds solutions from elements of a finite set of available solution components **C** = {*cij* }, *i* = 1, . . . , *n*, *j* = 1, . . . , |**D***i* | . The *i* and *j* represent the start end ending points or nodes respectively. The solution building process starts from an empty partial solution $s^p = ø$. At each building step, the partial solution s^p is extended by adding a feasible solution component from the set $\mathbf{N}(s^p) \subseteq$ **C**, which is defined as the set of components that can be added to the current partial solution s^p without violating any of the constraints in Ω.

  The ants select the following node to be visited through a stochastic mechanism. When ant *k* is in node *i* and has so far constructed the partial solution s^p, the probability of going to node *j* is given by equation 6:

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\propto} n_{ij}^{\beta}}{\sum_{c_{il} \in N s^p} \tau_{il}^{\alpha} \eta_{il}^{\beta}} & , \text{ if } c_{ij} \in N\,(s^p) \\ 0, & \text{otherwise} \end{cases} \qquad (6)$$

- Second phase*: Apply Local Search*: This phase is not always present in all the ACO algorithms. This step is used to improve the already acquired solutions through a local search.
- Third Phase: *Update Pheromones*: In this phase the pheromone values are decreased through the pheromone evaporation parameter or increased if the set of solutions is a promising one. Equation 7 shows the formula for updating the pheromone.

$$\tau_{ij} \leftarrow (1-\rho) * \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{7}$$

- ρ is the evaporation rate,
- m is the number of ants, and $\Delta\tau_{ij}^{k}$ is the quantity of pheromone laid on edge *(i, j)* by ant *k*

A flowchart summarizing what is explained before is shown in figure 12; wherever it says cities it is the same thing as saying nodes. The terminology depends on the context of the problem.

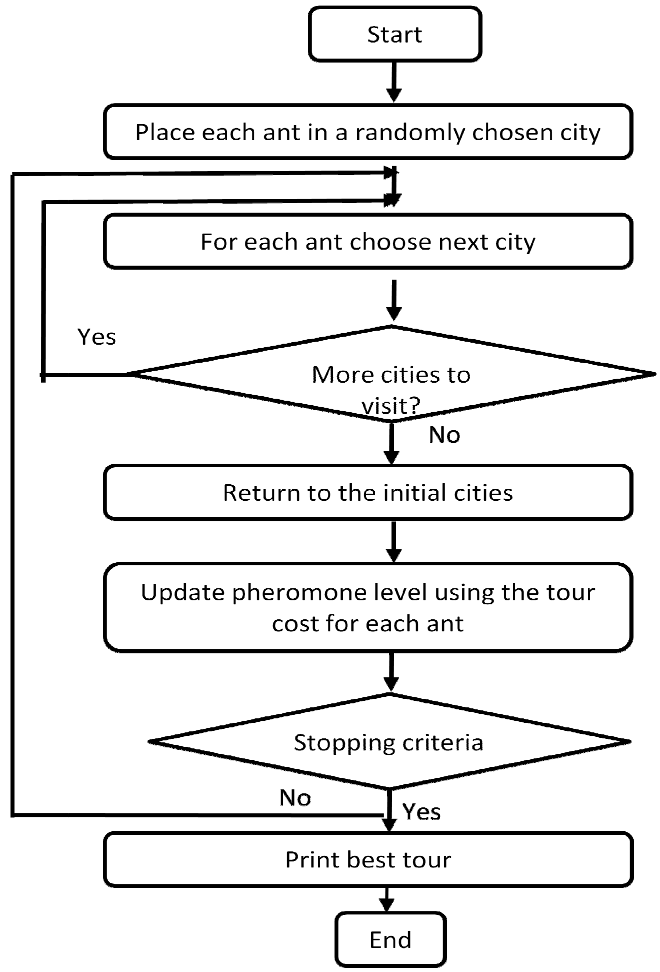

Figure 12: ACO flowchart

CHAPTER 3: Redundancy Allocation Problem

The redundancy allocation problem (RAP) is a reliability optimization problem composed of multiple *k*-out-of-*n* redundant subsystems arranged in a series configuration. The RAP is considered to be an NP- hard optimization problem [6]. It pertains to a system of s subsystems arranged in series. For each subsystem, there are m_i functionally equivalent components, with different levels of cost, weight, and reliability which may be selected. In the literature of RAP, many structures can be found depending on system configurations including series–parallel, hierarchical series–parallel or complex systems [2]. The structure that is followed in this work is a series- parallel system. This kind of system encloses several components connected in series, such that each series component can be connected into numerous elements connected in parallel. Such problems of maximizing system reliability through redundancy and component reliability choices are called the ‘‘reliability-redundancy allocation problem’’ [22].

The whole purpose is to maximize reliability and evade the shutdown or the failure of the system being analyzed. For each of the components that pertain to the RAP, there are several offered options from different vendors available to suit the distinct necessities of each system. Each option is characterized of its own reliability, its specific cost and particular weight. Later on an example clarifying this interpretation will be shown. Figure 13, illustrates a series- parallel configuration.

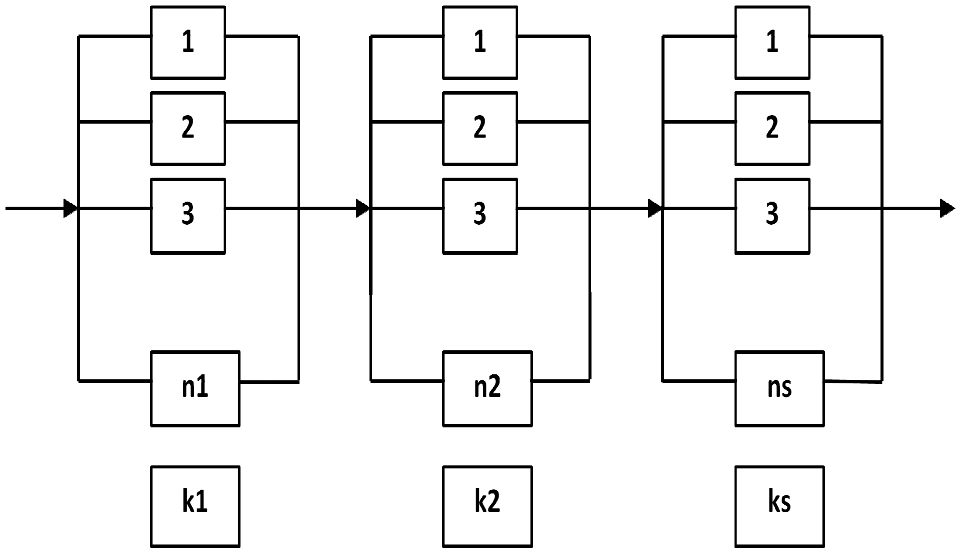

Figure 13: Series Parallel Configuration

As said earlier there are two different approaches to the Redundancy Allocation Problem, the single objective formulation and the Multiple Objective formulation. The single approach takes in consideration just the maximization of reliability for the system in question or the minimization of the total cost of the system. Another case can be the aggregation of these two objectives as one objective; this case will be explained in detail in the next section. The multiple objective version of the redundancy allocation problem addressed in this thesis involves the simultaneous optimization of system reliability, system cost and system weight [32]. This multi-objective problem clearly shows multiple conflicting objectives in which the reliability of the system can be improved by adding extra components but the cost and the weight are increased also. RAP is becoming an increasingly important tool in the initial stages of or prior to the planning, designing and control of systems [38].

3.1 Redundancy Allocation Problem Single Objective Approach

When talking about the Redundancy Allocation Problem, it is typical to think on enhancing the reliability of a system, at the lowest cost, but with this thinking we are assuming that we need to satisfy two objectives, the first one will be achieving a high reliability, while the second one will be spending the least amount of money possible.

For the last thirty years or so there have been several investigations in the RAP field. The disadvantage is that often the problem is treated as a single objective problem with the only goal of maximizing reliability or minimizing the total cost of the system design [37]. It is seen as a disadvantage because in reality we do not deal with single objective problems but in fact we expect that the final outcome of a problem or situation gives us satisfactory solutions from which the decision maker or stakeholder decides what the most suitable answer according to their expectations is.

The single approach of the RAP has its variants. The first and classic approach, is when the problem is treated as a single objective, meaning that either the maximization of reliability or minimization of cost are involved, each of them separately, or the second case where the two objectives are joined making one combined objective and then solved as a single objective problem by the mathematical methods already discussed in the previous sections, Another technique is where constraints are used, just one objective is taken in consideration for optimization and the others are used to restrain the search space.

A mixed of this possibilities for solving the RAP as a single objective problem is seeing in (Dhingra 1992) [10] where at first the problem is treated as a multiple objective problem, then they use goal programming in order to decide which objective has the highest weight and now treat the problem as a single objective, after that constraints are used to limit the search space and help in the achievement of a suitable solution.

3.2 Redundancy Allocation Problem Multiple Objective Approach

In the past, numerous approaches have been developed by many authors to solve the RAP, specifically, taking in to consideration the maximization of reliability, the minimization of cost and minimization of weight. When there is more than one objective to be optimized we call it a multi-objective formulation, and there are several methods to solve this type of problems. The two distinct categories are: mathematical and metaheuristic techniques. Some of the mathematical techniques used to solve the RAP include dynamic programming, integer programming, mixed integer and nonlinear programming models.

Metaheuristic's approaches have also been used. For instance, (Coit and Smith 1996) [8] used genetic algorithms (GA). (Kulturel-Konak, Smith and Coit 2003) [21] Applied their algorithm to three distinct RAP problems and compared the results with those of integer programming. (Ouzineb, Nourelfath and Gendeau 2008) [27] Used Tabu search considering availability constraints. (Liang and Smith 2004) [23] solved the RAP using Ant Colony Optimization (ACO), and (Taboada and Coit, Data Clustering of Solutions for Multiple Objective System Reliability Optimization Problems 2007) [31] used the Non- dominated sorting genetic Algorithm (NSGA) to find Pareto optimal solutions and then pruned them to minimize the search space to obtain a smaller number of solutions Hybrid approaches that use a combination of mathematical techniques and metaheuristic approaches have also been developed. For instance, (Tian and Zuo 2006) [34] combined genetic algorithms and programming techniques to find an optimal solution to the multiple objective redundancy allocation problem. A Particle Swarm Optimization (PSO) technique along with a mixture of integer programming was proposed by (Coelho L. 2009) [7]. All of the multi objective optimization methods already mentioned are examples found in the literature. The multi-objective RAP is used to show the performance of the new developed algorithm.

CHAPTER 4: Echolocation

4.1 Echolocation Principle

Echolocation is a mechanism used by several animals to locate their prey, navigate and simply to see in very dark environments [18]. Such animals that utilize this method include: dolphins, birds, shrews and bats. Despite the differences among the environments in which these animals prey they have evolved sonar systems, known as echolocation [26]. Bats will be a fundamental part of our study and will be discussed in the next subsection.

This biosonar, which is another name for it, is a navigational system that permits the localization of any kind of object, in different kind of environments such as: oceans, caves, undergrounds, or anything that has limited or none-existent light.

The basic principle of this method is the use of echoes. When a sound strikes an object, the sound bounces back, or reflects. The returning sound is called an echo. There are two important parameters, the time delay and the loudness of the echo. The first one, is the time that it takes for the sound to bounce back as an echo, and determines how far the object is located. The measurement of this time delay between the bouncing of the sound is called ranging. The second one is the loudness, and with this parameter the animal can determine the size of the object, the distance from where it is located and even its' texture [35].

Echolocating animals have two ears positioned slightly apart. The echoes returning to the two ears arrive at different times and at different loudness levels because it depends greatly on the position of the entity or object generating the echoes. The time delay and loudness differences are used by the animals to perceive direction. With echolocation, the bat or other animal can see and distinguish the position, distance, direction, size, surface, velocity and texture of the object.

4.1.1 Echolocation in Bats

Bats are extremely social creatures that spend much of their lifetime echolocating in the presence of other bats [17]. From all the species of bats, micro bats from the suborder Microchiroptera [18], are the ones that use echolocation to navigate and find food, objects, prey or obstacles in the darkness of their environments. As the bat approaches the target, the sonar pulses are emitted faster with a shorter duration. This happens until the bat is relatively close to the prey. Then, the bat grasps the insect up between its wings and into its awaiting mouth, as Kruse says "It is s a beautiful, complicated and highly accurate form of prey capture that is thoroughly supported by the bat's innate neural mechanisms" [20].

The principle of echolocation allows the bats to find food at night, when there are fewer predators, and there is less competition for food. Some researchers believe that bats evolved the use of this mechanism because birds, which are better predators, always won in the fight for food. Therefore, bats developed this mechanism in response to their environment and competence for food. These bats generate ultrasounds via the larynx and emit the sound through the open mouth or, much more rarely, the nose. Range in frequency from 14,000 to well over 100,000 Hz, mostly beyond the range of the human ear where typically a human hearing range is considered to be from 20 Hz to 20,000 Hz. These bats produce a bisonar sound consisting of a constant frequency portion (CF) followed by a downward frequency modulated sweep (FM). This releasing of sounds classifies them as a CF-FM type of Bat. The constant frequency portion of a pulse is great for detecting targets and measuring the Doppler shift. The FM portion of a pulse is excellent for perfecting on the distance of an object or obstacle and some of its details; such as the size and texture.

When a bat begins to echolocate, it usually produces short millisecond long pulses of sonar and listens to the returning echoes. If a prey is detected by the bat, it will generally fly

toward the source of the echo continuing to emit sounds and focus more accurately on the prey. As the bat advances to the target, the sonar pulses are emitted faster with a shorter duration. This happens until the bat is right upon the prey.

When the bat produces a CF-FM pulse, it also produces harmonics of that pulse. Consequently the bat is not only getting information from its first frequency, but also the 2nd, 3rd, and 4th frequencies of that pulse as we can see in figure 14.

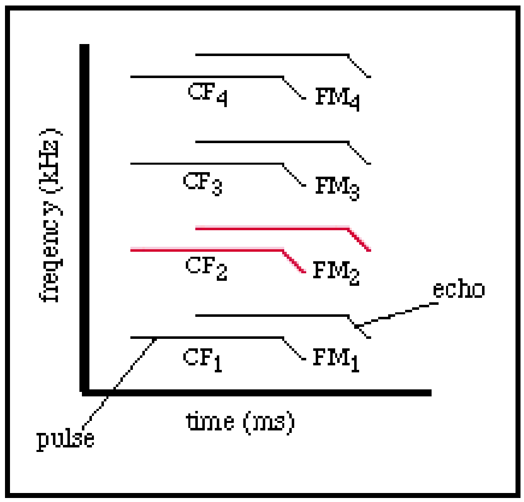

Figure 14: Frequencies

Of particular interest to the bat are the echoes returning from its 2nd harmonic pulse. This echo returns to the bat with a great deal of information about the Doppler shift of the objective. And there is a large specialization in the auditory cortex of the bat that focuses on the frequency range of this echo [20].

4.2 Model Development

The multi-objective formulation used in this thesis involves the maximization of system reliability, the minimization of system cost, and the minimization of system weight. For each

subsystem, there are m_i available components to choose from, and the maximum number of components that can be chosen is $n_{max,i}$. The multi-objective formulation is shown in Equation 8:

$$\max\left[\prod_{i=1}^{s} Ri(xi \mid ki)\right], \min\left[\sum_{i=1}^{s}\ \sum_{j=1}^{mi} c_{ij}x_{ij}\right], \min\left[\sum_{i=1}^{s}\ \sum_{j=1}^{mi} w_{ij}x_{ij}\right] \tag{8}$$

The first part of the equation is the maximization of reliability, where (*xi* / *ki*) denote the reliability of each component of each subsystem. The multi-objective version of the redundancy allocation problem involves the simultaneous optimization of system reliability, system cost and system weight. The RAP is considered to an NP-hard optimization problem (Chern 1992) [6]. The reliability of the system can be improved by adding extra components but the cost and the weight are increased also.

4.2.1 Notation and Assumptions

In the previous section the model followed in this work was presented, now the notation showed in the formulation and some extra notation use in the remainder of this paper will be considered in this section, and is as follows:

m = available components to choose from (j=1,2,3..)

x= vector containing components chosen for a specific subsystem (x_{11}, x_{12},..., x_{ij})

s= number of subsystems (i=1,2,3..)

n= number of components per subsystem

R(x) = Reliability of the system

C(x) = Cost of the System

W(x) = Weight of the System

Assumptions:

- The repair of any component is not considered
- Duplication and mixed is allowed
- At least one component per subsystem is needed

4.3 Solution Encoding

Each candidate solution to the redundancy allocation problem consists of the following equation $n_i = \sum_{j=1}^{mi} x_{ij}$ components in parallel ($k_i \leq n_i \leq n_{max,i}$) for each subsystem. The n_i components can be any combination of the components chosen from m_i available components. The candidate solution is encoded in a vector with s x $n_{max,i}$ positions. An index of 0 is assigned to a position when no additional component is used, i.e. $n_i < n_{max,i}$. The vector is completed by putting the solution representation of each subsystem adjacent to each other.

For example the vector x= (110 | 123 | 32) represents a possible solution with two of the first available components connected in parallel for the first subsystem; one of the first available components, one of the second available components and one of the third available component connected in parallel for the second subsystem, and one of the third available component, and one of the second, available components connected in parallel for the third subsystem. It is important to note that the available components are indexed independently for each subsystem. Therefore, the first available component in the first subsystem is not the same as the first available component in the second subsystem, and they are not the same as the ones in the third subsystem.

4.4 Echolocation-based Evolutionary Search Algorithm: Methodology

Mimicking the echolocating animal, say a bat, that searches for its prey using ultrasound beams with a certain angle and two ears, the proposed algorithm searches for the optimal solution using a certain degree of angle and its two boundaries. The following steps show how the proposed algorithm was developed using the multiple objective redundancy allocation problem as example. Each available solution is a combination of the available components for each subsystem. In this case, we take into consideration a system composed of three subsystems. Furthermore the configurations that are shown in Figures 20 and 21 represent the available component option of the subsystem depending in which place it is located. This will be explained in detail in the following paragraphs.

Step 1. Divide the search space. It is assumed the full angle of the search space =180˚, as seen in figure 15. As the algorithm looks for solutions, the angle becomes smaller and smaller, until it reaches the final configuration that we are looking for. Also the angle becomes so small that is close to zero, and that means that the bat reached its prey, and in our case that we reach an optimal solution.

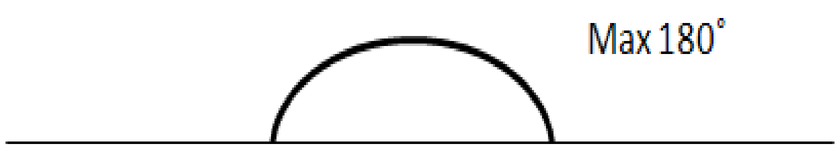

Figure 15: Full Angle of Search Space

Step 2. Each subspace has five candidate solutions inside the dividing lines. This process is used to mimic how the bat receives echoes, which arrive at different times and loudness, as Figure 16 shows. Because in this paper we are considering multiple objective functions to be

optimized simultaneously, the fitness of each candidate is evaluated according to an aggregated fitness function.

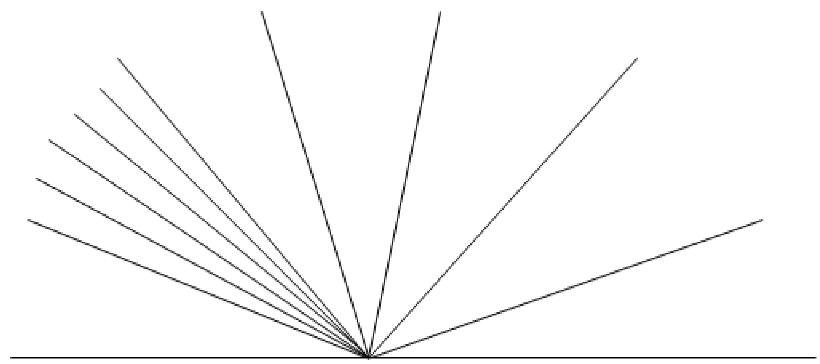

Figure 16: Search space being explored by different angles

Step 3. The fitness values of all the candidate solutions at the boundaries of all subspaces are then evaluated using two different fitness metrics as proposed in (Taboada and Coit, A New Multiple Objective Evolutionary Algorithm for Optimal Redundancy Allocation 2010) [30]. The dominance count and the distance based explained next.

Fitness metric 1 ($f_1(x)$):

- Dominance-count
  - The solution that dominates more solutions has a better fitness, as illustrated in figure 17, L1 dominates L2 and the solutions above them, on the other hand L2, just dominates the solutions above L2, and so on.

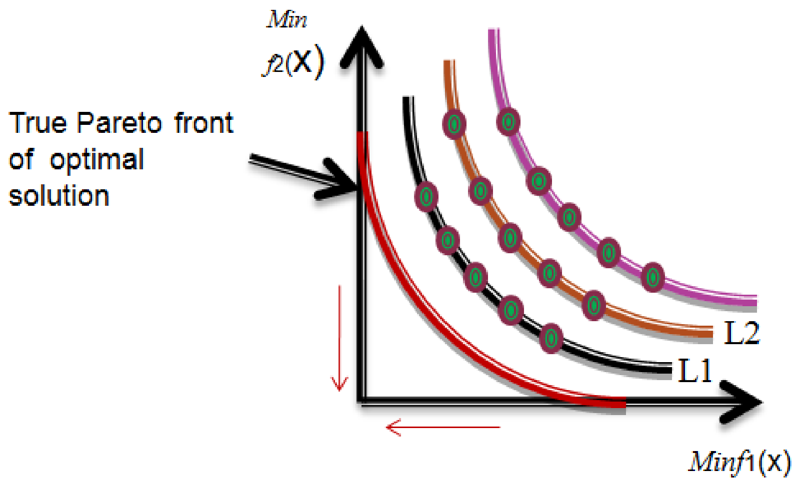

Figure 17: Dominance Count

Fitness metric 2 ($f_2(x)$):

- Distance based
  - This fitness metric gives a highest fitness value to those solutions that are farther away from other solutions in the Pareto front; this fitness metric permits the achievement of diversity among the solutions. Figure 18 illustrates this.

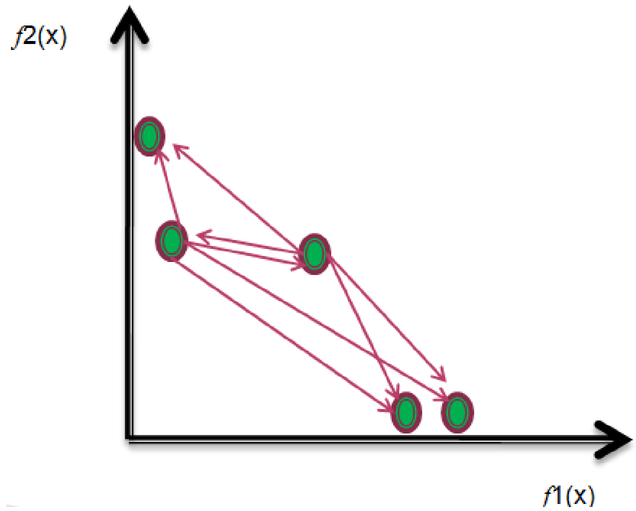

Figure 18: Distance based

Once we have calculated the two fitness values, then we aggregate them into a single value called the aggregated fitness function, this is illustrated in figure 19.

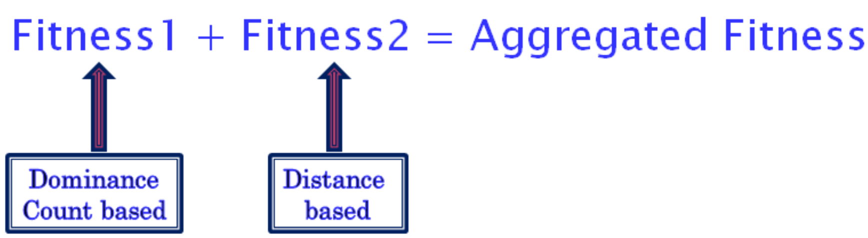

Figure 19: Aggregated Fitness

Step 4. Once an aggregated fitness value has been calculated, we select to further explore the sub-space with the best fitness value as shown in Figure 20. In this figure, we can see that each sub-space has a combination of several numbers. The numbers depend on the problem being examined, in this case since the problem has a maximum of seven components per subsystem each vector containing a possible answer to the problem consists of a maximum of seven numbers and if one position is filled with a zero, that means that there is no

component needed. These combinations are the possible solutions of the problem. As it is stated earlier in the problem the example consists of three subsystems. And the numbers displayed are the numbers that represent a component available to buy from a vendor. The first subsystem can be built with a maximum of three components, while subsystems two and three can be built with a maximum of two components. Each number in the vector is a representation of the design alternative that we can choose from, and those alternatives are available in table 1.

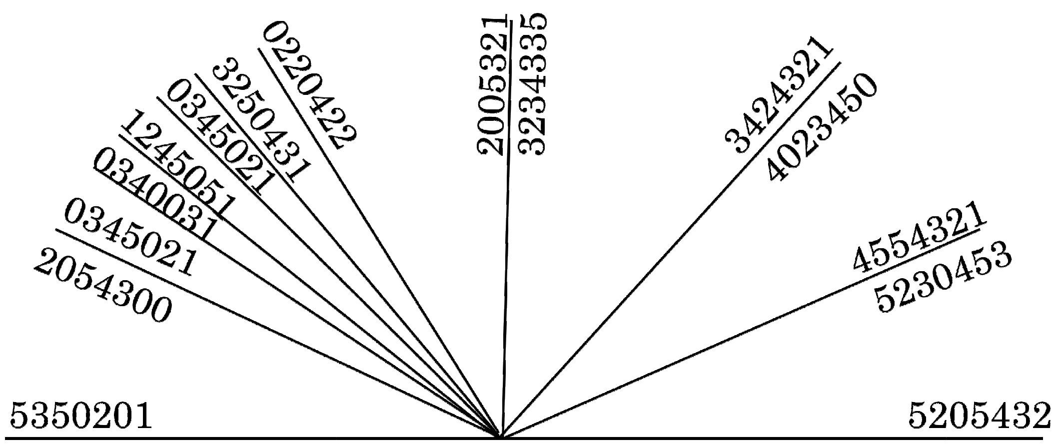

Figure 20: Subspaces

Table 1 below shows us the different vendors and components that we can choose from.

Table 1: Available Components from Vendors

Design alternative *j*	**Subsystem *i***								
	1			2			3		
	R	*C*	*W*	*R*	*C*	*W*	*R*	*C*	*W*
1	0.94	9	9	0.97	12	5	0.96	10	6
2	0.91	6	6	0.86	3	7	0.89	6	8
3	0.89	6	4	0.70	2	3	0.72	4	2
4	0.75	3	7	0.66	2	4	0.71	3	4
5	0.72	2	8				0.67	2	4

For instance, referring to figure 21 and 22 the first combination represented in vector: (102 05 35) means that the first component of the first subsystem is going to be component one, and the third component of the first subsystem is component two, Then, the second subsystem is built with a copy of component five as the second component; while the third subsystem is built with one copy of component three in first place and a copy of component five in second place.

Step 5. Then more random solutions are generated but now the first component is fixed according to step number 4, where the sub-space with better fitness value is chosen to be further explored as Figure 21 shows.

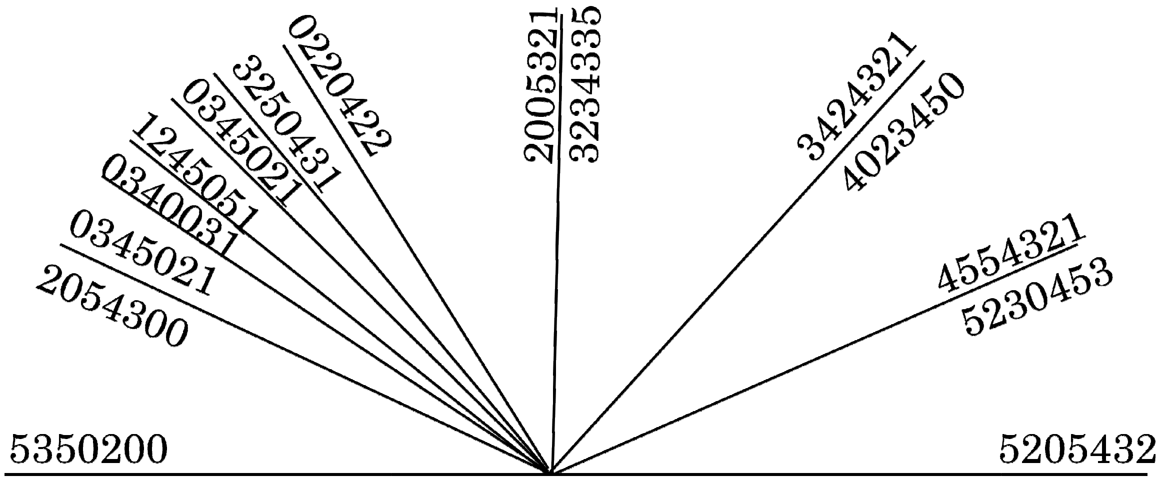

Figure 21: Generation of more solutions

Step 6. Again back to step 1: A new angle (sub-angle) is explored illustrated in figure 22 and previous steps are repeated until we get more solutions. The algorithm is able to obtain one solution at each of the iterations, and then it has to be run several times to get a Pareto-optimal set.

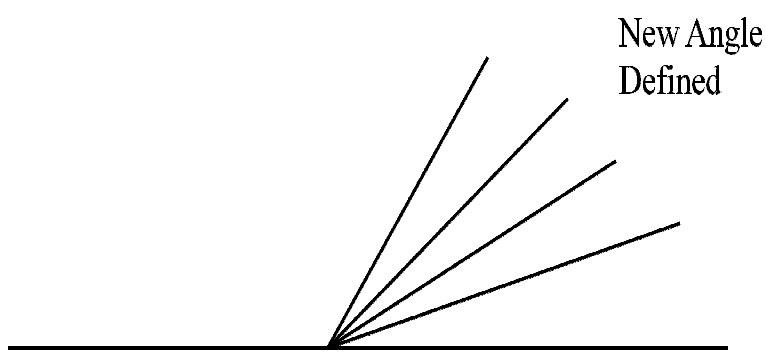

Figure 22: New angle defined

CHAPTER 5: Illustrative Example

In this chapter the performance of the algorithm previously explained and illustrated is going to be demonstrated using the Redundancy Allocation Problem (RAP) in its multi-objective formulation. The objectives to be optimized are the following:

- Maximization of Reliability R(x)
- Minimization of Cost C(x)
- Minimization of Weight W(x)

The system solved is a series-parallel system, with three subsystems arranged in series. A maximum of eight components can be chosen to be arranged in parallel for each subsystem as shown in Figure 23.

Subsystem one has a maximum of five design alternatives for the allocation of components, subsystem two has a maximum of four design alternatives, and subsystem number three has a maximum of five alternatives as well as subsystem one. For the three subsystems, duplication and mix of the components are allowed.

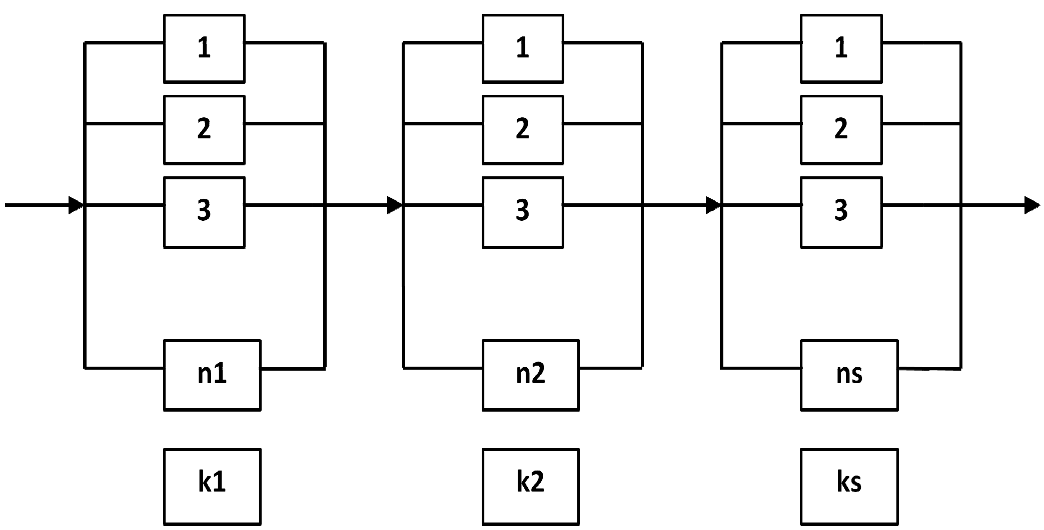

Figure 23: Illustrative Example

Table 2 presents the information of the component reliabilities, cost and weight used in this thesis to illustrate the performance of the Echolocation –based Evolutionary algorithm.

Table 2: Available Components from vendors

Design alternative *j*	**Subsystem *i***								
	1			2			3		
	R	*C*	*W*	*R*	*C*	*W*	*R*	*C*	*W*
1	0.94	9	9	0.97	12	5	0.96	10	6
2	0.91	6	6	0.86	3	7	0.89	6	8
3	0.89	6	4	0.70	2	3	0.72	4	2
4	0.75	3	7	0.66	2	4	0.71	3	4
5	0.72	2	8				0.67	2	4

5.1 Results

After running the algorithm, fifteen solutions were found in the Pareto-optimal set of solutions. The fifteen solutions obtained are shown in Table 3. As it can be seen, all of these solutions are nondominated solutions. A nondominated solution is a solution that is not dominated by any other in the solution space and therefore, in the absence of any judgmental information, no solution is said to be better that any other in the Pareto set.

The solution to the multi-objective problem presented in this paper is the Pareto-optimal set of solutions shown in a three-dimensional graph in Figure 24 and in figure 25 the two-dimensional views are shown. Once the Pareto-optimal set has been obtained, an additional method needs to be used for post-Pareto analysis, either to reduce the number of solution of

the Pareto set, or to select one solution for system implementation. Post-Pareto optimality is out of the scope of this research. Even though, at the end of this section a solution was chosen. However, there are numerous methods in the literature developed for this purpose, which can be discussed for future research.

Table 3: Non dominated Solutions found in Pareto Set

Solution	Reliability	Cost	Weight
1	0.991	48	59
2	0.9967	69	64
3	0.9965	47	74
4	0.996	61	48
5	0.9689	58	58
6	0.9971	72	57
7	0.9921	67	69
8	0.9172	35	54
9	0.8982	29	39
10	0.9562	44	53
11	0.9922	44	65
12	0.9866	54	57
13	0.9947	51	64
14	0.9681	45	49
15	0.9968	54	68

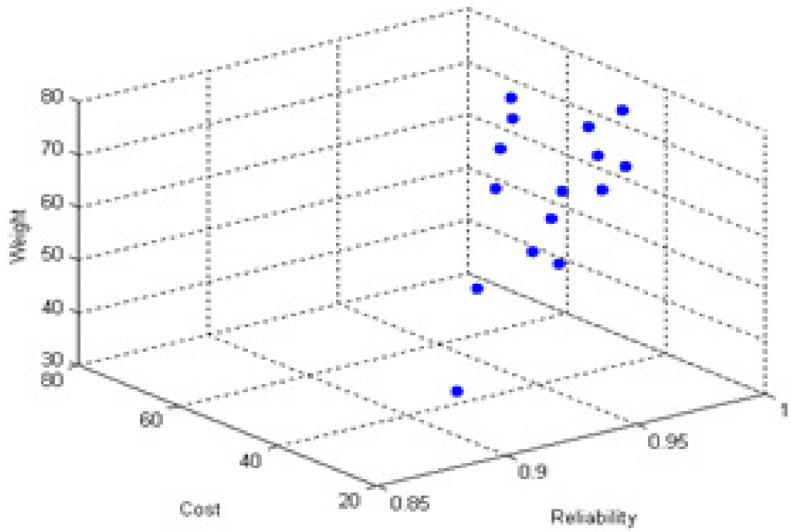

Figure 24: Pareto Set of Solutions 3D view

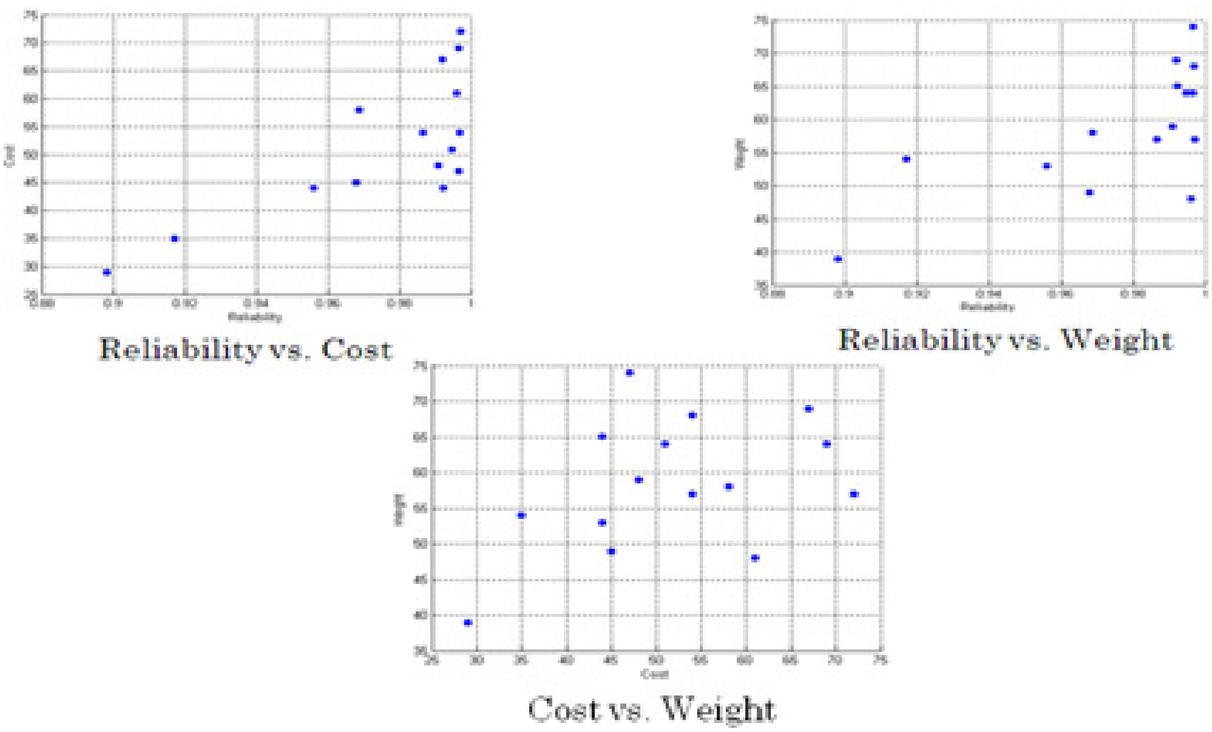

Figure 25: Pareto Set of Solutions 2D views

As it is shown in the results above, the algorithm found a Pareto front with several optimal results; this means that there is no possibility of getting better values for any objective without the worsening of the others. Every combination presented has the best fitness values for each objective. All of them are non-dominated solutions and the next step is to select just one solution among the set of solutions achieved. In order to make the selection the decision maker needs to decide among the different techniques available in the literature.

One technique is a Data Clustering Approach [31] in this technique the results are clustered according to the similarities between the solutions. In this manner the Decision maker has a short range of possibilities to choose from and also evades the creation and allocation of weights, in order to decide which objective is more important on top of the others.

In order to choose the point presented in figure 25, a normalization of the objectives had to be done first, then we selected the combination that was closest to our ideal point which in this case is [1, 0, and 0]. This represents 1 for Reliability, 0 for cost and 0 for weight. In order to decide which point was closest to the ideal point we used Euclidean distance to determine the shortest distance in between the solutions and the ideal point, and figure 26 shows the selected configuration of the solution closest to the ideal point with its respective reliability, cost and weight values.

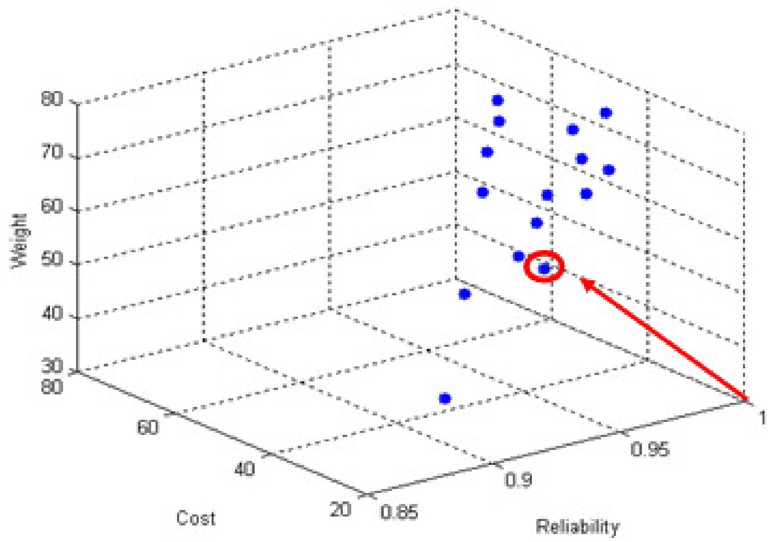

Figure 26: Closest Point to ideal Point

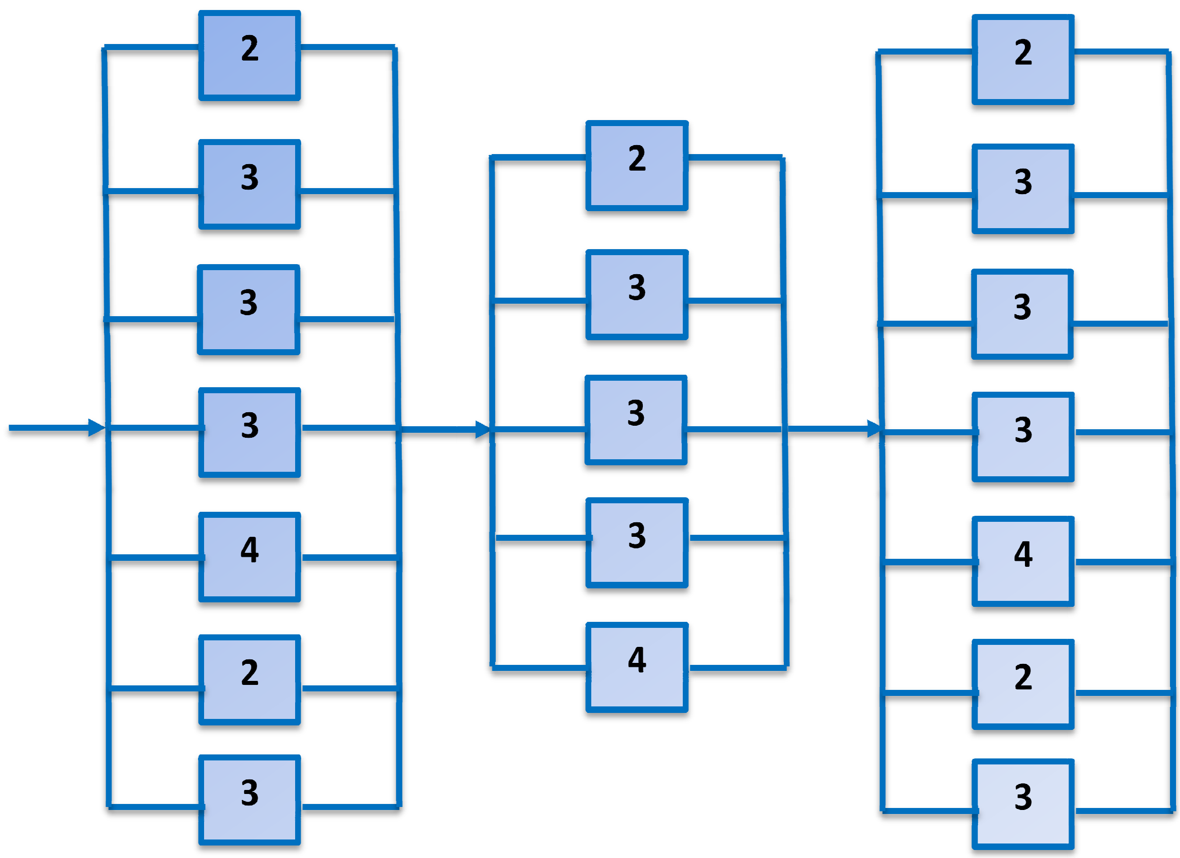

Figure 27: Selected Configuration

Reliability = 0.9681

Cost = 45

Weight = 49

Chapter 6: Conclusions and Future Research

After a brief introduction of this work presented in chapter 1 basic concepts on single and multiple objective optimization techniques were presented in chapter 2. Sequentially, in Chapter 3, the redundancy Allocation Problem in its two different variances was presented. In chapter 4 A new developed algorithm and the basic concepts was proposed. In order to show the performance of the algorithm an example was offered in chapter 5. And, finally, in this section conclusions and future research will be presented.

This thesis presented a newly developed algorithm based on the principle of echolocation. Where the bats emit ultrasound beams with a certain degree of angle and multiple receivers; such as their two ears that are located slightly apart. With this said the algorithm searches the solution space within an initial angle of 180 degrees. Because bats have a sight of no more than 180 degrees; therefore a greater angle is not utilized. The algorithm developed and explained in this paper uses the echolocation principle in order to explore the search space to obtain an optimal solution.

The algorithm makes searches for possible solutions in different sub-spaces. Then it focuses the search where the best local solution has been found. The process continues until all the sub-spaces have been explored. As part of future research more different parameter will be explored and also more formal approaches for Post-pareto optimality.

References

1. Arunkumar, A, I Karunamoorthy, S Anand, and T Ramesh Babu. "Linear Approach for Solving a Piecewise Linear Vendor Selection Problem of Quantity Discounts Using Lexicographic Method." *International Journal of advanced Manufacturing Technology* 28 (2006): 1254-1260.
2. Beji, Noura, Bassem Jarboui, Mansour Eddaly, and Habib Chabchoub. "A Hybrid Particle Swarm Optimization Algorithm for the Redundancy Allocation Problem." *Journal of Computational Science* 1, no. 3 (2010): 159-167.
3. Bland, J. A., and G. P. Dawson. "Tabu Search and Design Optimization." *Computer Aided Design* 23, no. 3 (1991): 195-201.
4. Brandimarte, Paolo. "Neighbourhood search-based optimization algorithms for production scheduling: a survey." *Computer Integrated Manufacturing Systems* 5, no. 2 (1992): 167-176.
5. Charnes, A, W. W. Cooper, and R. Ferguson. "optimal Estimation of Executive Compensation by Linear Programming." *Mangement Science* 1 (1955): 138-151.
6. Chern, M.S. "On the Computational Complexity of Reliability Redundacy Allocation in a Series System." *Operations Research Letters* 11, no. 5 (1992): 309-315.
7. Coelho L., D. S. "An Efficient Particle Swarm Approach for Mixed-Integer Programming in Reliability Redundancy Optimization Applications." *Reliability Engineering and System Safety* 4, no. 2 (2009): 830-837.
8. Coit, D., and A. Smith. "Solving the Redundancy Allocation Problem Using a Combined Neural Network/Genetic Algorithm Approach." *Computers and Operations Research* 23, no. 6 (1996): 515-526.
9. Collette, Yann, and Patrick Siarry. *Multiobjective Optimization.* Berlin: Springer, 2003.

10. Dhingra, Anoop k. "Optimal Apportionment of Reliability and Redundancy in Series Systems Under Multiple Objectives." *IEEE Transactions on Reliability* 41, no. 4 (1992): 576-582.

11. Dorigo, M, V Maniezzo, and A Colorni. "Ant System: Optimization by a Colony of Cooperating Agents." *IEEE Transactions on Systems, Man, and Cybernetics* 26, no. 1 (1996): 29-41.

12. Dorigo, Marco, Mauro Birattari, and Thomas Stutzle. "Ant Colony Optimization, Artificial Ants as a Computational Intelligence Technique." *IEEE Computational Intelligence* 1, no. 4 (2006): 28-39.

13. Eglese, R. W. "Simulated Annealing: A Tool for Operational Research." *European Journal of Operational Research* 46 (1990): 271-281.

14. Gao, X, and W Lou. "A New Crossover Operator in Genetic Programming for Object Classification." *IEEE Transactions on Systems, Man, and Cybernetics* 37, no. 5 (2007): 1332-1343.

15. Georgy, Maged E., Luh-Maan Chang, and Lei Zhang. "Utility Function Model for Engineering Performance Assessment." *Journal of Construction Engineering and Management*, 2005: 558-568.

16. Glover, Fred. "Heuristics for Integer Programming Using Surrogate Constaints." *Decision Sciences* 8 (1977): 156-166.

17. Jarvis, Jenna, Kirsten M. Bohn, Jedediah Tressler, and Michael Smotherman. "A Mechanism for Antiphonal Echolocation by Free-Tailed Bats." *Animal Behaviour* 79 (2010): 787-796.

18. Jones, Gareth, and Emma C. Teeling. "The Evolution of Echolocation in Bats." *TRENDS in Ecology and Evolution* 21, no. 3 (2006): 149-156.

19. Kim, I. Y., and O. I. de Weck. "Adaptive Weighted Sum Method for Multiobjective Optmization: in a new method for Pareto Front Generation." *Springer*, no. 31 (2006): 105-116.
20. Kruse, Amy. *Model systems in Neuroethology.* December 1996. http://nelson.beckman.illinois.edu/courses/neuroethol/models/bat_echolocation/bat_echolocation.html (accessed march 2010).
21. Kulturel-Konak, S., A. Smith, and D. Coit. "Efficiently Solving the Redundancy Allocation Problem using Tabu Search." *IIE Transactions* 23, no. 6 (2003): 515-526.
22. Kuo, W, and V.R. Prasada. "An Annotated Overview of System-Reliability Optimization." *IEEE Transactions on Reliability* 49, no. 2 (2000): 176-187.
23. Liang, Yun-Chia, and Alice Smith. "An Ant Colony Optimization Algorithm for the Redundancy Allocation Problem (RAP)." *IEEE Transactions on Reliability* 53, no. 3 (2004): 417-423.
24. Metropolis, Nicholas, Arianna Rosenbluth, Marshall Rosenbluth, and Augusta H. Teller. "Equation of State Calculations by Fast Computing Machines." *The Journal of Chemical Physics* 21, no. 6 (1953).
25. Michiels, Wil, Emile Aarts, and Jan Korst. *Theoretical Aspects of Local Search.* Germany: Springer, 2007.
26. Nihoul, J.C.J. "Echolocation in Bats and Dolphins Review." *Journal of Marine Systems* 50 (2004): 283-284.
27. Ouzineb, M., M Nourelfath, and M Gendeau. "Tabu Search for the Redundancy Allocation Problem of Homogenous Series-Parallel Multi-State Systems." *Reliability Engineering and System Safety* 93, no. 8 (2008): 1257-1272.

28. Prats, Xavier, Vicenc Puig, Joseba Quevedo, and Fatiha Neijari. "Lexicographic Optimization for Optimal Departure Aircraft Trajectories." *Aerospace Science and Technology* 14, no. 1 (2010): 26-37.
29. Roy, Bernard, and Phillipe Vincke. "Multicriteria Analysis:survey and new directions." *Europena Journal of Operational Research* 8, no. 3 (1981): 207-218.
30. Taboada, H., and D. Coit. "A New Multiple Objective Evolutionary Algorithm for Optimal Redundancy Allocation ." *International Journal of Operations Research and Information System (under review)*, 2010.
31. Taboada, H., and D. Coit. "Data Clustering of Solutions for Multiple Objective System Reliability Optimization Problems." *Quality Technology and Quantitative Management* 4, no. 2 (2007): 191-210.
32. Taboada, H., F. Baheranwala, D. Coit, and N. Wattanapongsakorn. "Practical Solutions for Multiobjective Optimization: An application to System Reliability Design Problems." *Reliability Engineering and Systems Safety* 23, no. 6 (2007): 314-322.
33. Tamiz, Mehrdad, Dylan Jones, and Carlos Romero. "Goal Programming for Decision Making: An Overview of the Current State-of the -Art." *Europena Journal of Operational Research*, no. 111 (1998): 569-581.
34. Tian, Z., and M. Zuo. "Redundancy Allocation for Multi-state Systems using Physical Programming and Genetic Algorithms." *Reliability Engineering and Systems Safety* 91, no. 9 (2006): 1049-1056.
35. Vauhan, Terry A., James M. Ryan, and Nicholas J. Czaplewski. *Mammalogy.* Masachussetts: Jones and Bartlett Publishers, 1999.
36. Walker, I. *Reliability in Scientific Research.* New York: Cambridge University Press, 2011.

37. Wang, Zai, Tianshi Chen, Ke Tang, and Xin Yao. "A Multi-Objective Approach to Redundancy Allocation Parllel -Series Systems." *IEEE Congress on Evolutionary Computation*, 2009: 582-589.

38. Yeh, Wei- Chang, and Tsung-Jung Hsieh. "Solving Reliability Redundancy Allocatoin Problem Using an Artificial Bee Colony Algorithm." *Computers and Operations Research* 38 (2011): 1465-1473.

39. Zang, Hognian, Shujun Zhang, and Kevin Hapeshi. "A Review of Nature-Inspired Algorithms." *Journal of Bionic Engineering* 7 (2010): 5232-5237.

40. Zitzler, Eckart, and Lothar Thiele. "Multiobjectuve Evolutionary Algorithms:AQcomparative Case Study and the Strength Pareto Approach." *IEEE Transactions on Evolutionary Computation* 3 (1999): 257-271.

Vita

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