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Multi-State Multi-Objective Reliability Analysis Of Renewable Energy Systems

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MULTI-STATE MULTI-OBJECTIVE RELIABILITY ANALYSIS OF RENEWABLE ENERGY SYSTEMS

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DEDICATION

To my beloved parents, grandparents and siblings.

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by

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THESIS

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1. INTRODUCTION

1.1 Electricity Generation in the United States

The electricity generation in the United States has shifted throughout the years. In the early years, 1775, the main source of energy was wood. Nowadays, wood is the least consumed source in the country. Today, most of the electricity generated in the U.S. comes from fossil fuels. The term fossil fuel refers to a natural fuel which was formed in the geological past from the remaining of living organisms. The most common fossil fuels used are natural gas, coal and oil and they all fall under the category of Non-Renewable energy sources. Another way that electricity is obtained in the country is with nuclear power, where the nuclear power plant utilizes nuclear fission to create steam that spins a turbine to generate electricity. The first nuclear power plant in the country was opened in the year 1957. Furthermore, research has provided the opportunity to find new technologies in the energy generation sector. Renewable Sources, such as wind, the sun, and water, have been used to generate electricity, although some of these sources have been used since the 11th Century for the watermills or the windmills (U.S. Energy Information Administration). Currently, the electricity generation is clearly still dominated by non-renewable sources, but with the ongoing social movements to shift that trend to new approaches, the renewable sources will find its way to gaining terrain in the electricity production. With all the new technologies and methods for electricity generation, the main question is, how to handle these methods to make the best out of it?

1.2 Greenhouse Gas Emissions in the United States

The Greenhouse Gases are the gases that trap heat in the atmosphere, they allow the sunlight shine onto the Earth's surface but trap the heat that reflects up into the

atmosphere, therefore creating the greenhouse effect. The gases that make up the GHG are Carbon Dioxide (CO2), Methane (CH4), Nitrous Oxide (N2O) and Fluorinated Gases. The GHG emissions are released into the atmosphere by natural cause or by human activities (U.S. Energy Information Administration 2011). Animals and plants release carbon dioxide when they breathe, in addition, every time a volcano erupts, it releases carbon dioxide emissions. Low oxygen environments such as swamps, naturally release methane and nitrous oxide is naturally release from bacteria soil. In the other hand, since the Industrial Revolution (late 1700's, early 1800's) GHG emitted from human activity increased exponentially. The generation of electricity through the burning of fossil fuels, and the use of transportation such as cars, trains, buses and planes, all contribute to the release of carbon dioxide. Coal mining and natural gas processing contribute to the release of methane to the atmosphere as well as through livestock farming and landfills. Human activities such as agriculture, fossil fuel combustion and industrial processes are the primary cause of nitrous oxide concentrations in the atmosphere.

Countries across the globe contribute to the Greenhouse Gas Emissions. From data gathered from the International Energy Agency, in ***Figure 1***, it shows the top 10 countries with the most GHG emissions (U.S. Energy Information Administration 2015). A shocking statistic is that these top ten contributors are responsible for 73.01 percent of the total global emissions.

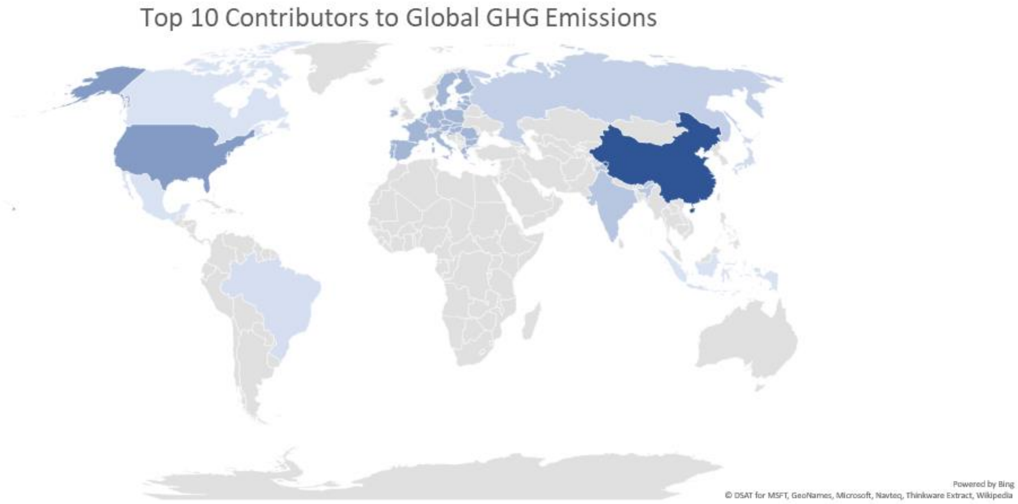

Figure 1: **GHG Global Emissions**

One thing they have in common is their primary emitter is the energy sector. Over the past fifteen years, the energy sector has prevailed as the leading contributor over any other sector, representing about 72 percent of the global emissions. ***Figure 2*** describes an indicator of Greenhouse gases worldwide (Environmental Protection Agency, 2017). With a brief comparison, it is easy to identify an increase of 11,767.9 million metric tons of carbon dioxide equivalent emissions emanated to the atmosphere. From various investigations and reports, this increase of emissions across the globe is said to be anthropogenic. Some of the human activities that affect the environment, resulting in the emission of greenhouse gases are: the extraction fossil fuels and their burning for electricity generation, deforestation, domesticated animals (livestock), agriculture practices, disposal and treatment of human waste, to mention a few.

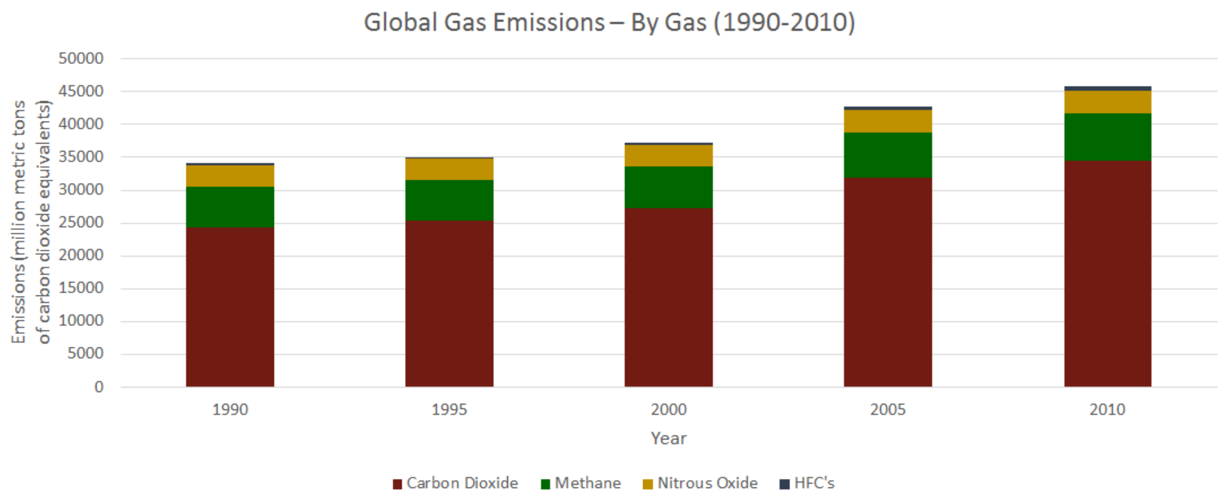

Figure 2: **Global Gas Emissions**

In the year 2015, former President Obama signed a plan of action, the Paris Agreement, where he declared that the country had to limit the amount of Greenhouse Gas Emissions (GHG) it generated from power generation plants, agricultural practices, transportation and other daily activities (United Nations Framework Convention on Climate Change). After this action, it has proceeded sundry number of protests and rallies both in favor and against the action taken from the former president of the United States. As of today, President Obama's successor, President Trump, has taken action to try and withdraw the country from the Paris Agreement; despite his efforts, there has not been any success. In recent years, Greenhouse Gas Emissions have been part of a major topic involved in politics, research and technology. ***Figure 3*** shows the percentage of gas emissions.

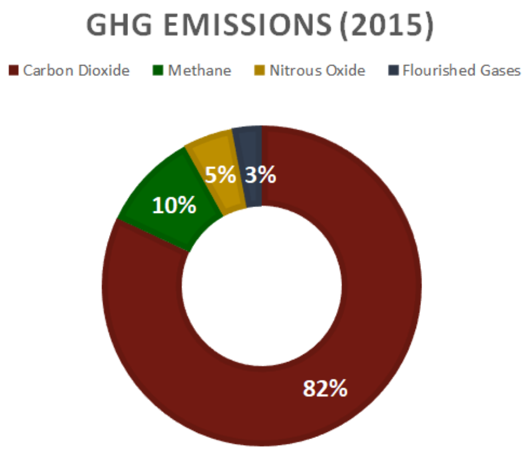

Figure 3: **GHG Emissions in the US**

The gas with most of the emissions in the country is Carbon Dioxide with 82 percent of the total emissions, followed by Methane, Nitrous Oxide and Fluorinated Gases. It is important to put in perspective the substantial amount of emissions in the country by comparing them with, perhaps, more common daily activities. From the 82 percent of Carbon Dioxide, it yields about 5,401.34 million metric tons of CO2 equivalence, which is about the total CO2 emissions of 809,553,357 homes' electricity use for one year. The 10 percent of CH4 is about 658.7 million metric tons of CO2 equivalence which yields about a total of 98,726,019 homes' electricity use for one year. Nitrous oxide total CO2 equivalent emissions is 329.35 million metric tons, these numbers would generate about 49,363,010 homes' electricity use for one year. Finally, Fluorinated Gases 3 percent of GHG emissions produce about 197.3 million metric tons of CO2 equivalence, something akin will be the 29,572,842 homes' electricity use for one year (Environmental Protection Agency, 2018). ***Figure 4*** has broken down the sources of the GHG emitted in the United States from the latest recording in the year 2015.

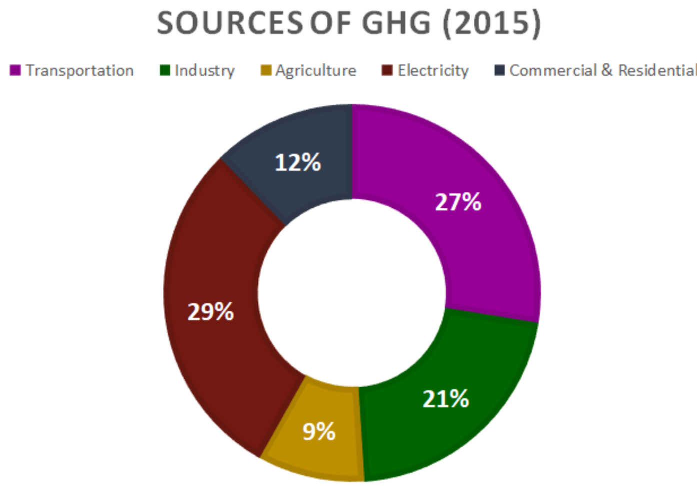

Figure 4: **GHG Sources**

In the United States the majority of the GHG emitted to the atmosphere come from the Electricity generation sector with 29 percent from which includes the extraction and burning of fossil fuels (natural gas and coal) (U.S. Energy Information Administration). Followed by Transportation which consist in any matter of transportation that uses gasoline or diesel such as our daily car or truck, as well as any ship, airplane or train. The Industry which accounts for 21 percent of the emissions, which are categorized in direct and indirect emissions. Direct emissions are produced by burning fuel for power or heat, or leaks from industrial processes while indirect emissions are caused by the burning of fossil fuels to power the industrial facility. Commercial & Residential are responsible of 12 percent of the total emissions, such emissions are generated from heating, cooking, organic waste and wastewater, to mention a few. Finally, Agriculture activities, such as livestock, burning of crops, and cultivation of some products make up 9 percent of the total emissions in the country. In 2015, the total emissions were 6,587 Million Metric Tons

of CO_2 Equivalent, which is an equivalent of the total emissions generated from 16,144,607,843,137 miles driven by an average passenger vehicle. Each activity emits a different kind of gas into the environment and each gas has a different level of impact into the environment.

The past different administrations that have served the United States, they all have implemented different methods to counter the negative data in Greenhouse Gas emissions. Through agencies, such as the Environmental Protection Agency (EPA), the government has enforced initiatives like the Clean Power Plan, which constraints power plants to cut carbon pollution, or the joint effort from the EPA and the National Highway Traffic Safety Administration (NHTSA) to enable the production of clean vehicles. In some way, the government has imparted some action to minimize anthropogenic emissions. It is true, that our world is still ruled by fossil fuels, but, it is necessary to start thinking about a world with new, clean technologies. Nowadays, one of the biggest queries is to define what route the country will be taking, despite all the efforts and laws passed in favor of the usage of clean energy and reduction of GHG emissions, will the country keep on using fossil fuels as the main source of energy or will it make a swift to renewable sources?

1.3 Multiple Objective Optimization

Multiple objective evolutionary algorithms are some of the most common tools used and developed by engineers to solve complex optimization problems that have more than one simultaneous objective function to resolve. For instance, a product with great performance is also a product with a high cost and the customer is always looking for a great product with the lowest price. It is a broad field and that is why the research in multi-objective optimization problems has risen since its development. The usage of Multiple

Objective Optimization methods is widely used in different fields, such economics, finance, engineering among others.

Because of the complexity of the problems treated, the answer does not consist of a single solution, rather, a set of solutions, also called a Pareto Front. The set of solutions consists of a number of nondominated solutions. For a solution to be considered a nondominated solution, solution x_1 dominates solution x_2, two conditions must be met.

- Solution x_1 is no worse than x_2 in all objectives
- Solution x_1 is strictly better than x_2 for at least one objective

Therefore, a single solution on a Multi-Objective problem does not exist. The solutions in the Pareto Front represent the best results possibly obtained considering all of the objective functions (Deb, et al, 2014).

In present day, there exist an ample number of methods used in multi-objective optimization problems. Some of the simple methods, such as goal programming and the weighted sum method, among others, however, occasionally do not evaluate all of the objectives concurrently, making them unreliable. Metaheuristic methods, on the other hand, approximate solutions to the Pareto Front. The uniqueness of the Metaheuristic methods is the mimicking of animal behavior, music, human behavior, etc. Some of these methods include, particle swarm, ant colony, bee colony, simulated annealing or harmony search optimization methods. These methods do not guarantee the finding of the optimal solution, nevertheless, the solutions found in complex problems tend to be favorable.

In extension to metaheuristic optimization methods, multi-objective optimization methods have also implemented evolutionary algorithms. These types of algorithms are a population-based method that imitates Darwin’s theory of evolution: an organism,

through natural selection, develops modifications to preserve in order to reproduce. These types of algorithms are called multiple objective evolutionary algorithms (MOEA's) and among the most popular include the Strength Pareto Evolutionary Algorithm (SPEA), Pareto Archived Evolutionary Strategy (PAES), Pareto-envelope, based selection algorithm (PESA), among others (Das, et al, 2009).

1.4 Thesis Objective

As will be seen in future chapters, it is noted that the use of renewable energies has increased in the past 20 years. This increase brings into the table an opportunity to develop new ways to simulate and determine the reliability of a multi-state renewable energy system while considering the maximization of the probability of meeting a demand and the minimization of applied cost. Chapter 2 will talk about the use of non-renewable energy sources in the country. Similarly, Chapter 3 will cover the usage of the renewable sources in the United States. Additionally, Chapter 4 explains different kinds of metaheuristic algorithms and their application in different fields, while Chapter 5 will explain the Universal Generating Function (UGF). Chapter 6 shows some similar work done using the UGF in the reliability field. Moreover, Chapters 7 & 8 will present two different Case Studies in which the UGF is used to obtain the reliability of a system. Finally, Chapter 9 gives a conclusion of the results obtained.

2. NON-RENEWABLE ENERGY IN THE UNITED STATES

Non-Renewable energy comes from sources that will, at some point run out, or take thousands and even millions of years to restore. Most non-renewable sources are fossil fuels: natural gas, coal, and petroleum. An important distinction in fossil fuels is that their main element is carbon. These sources were formed about 359.2-299 million years ago, during the Carboniferous Period. During this period, the world was full of swamp forests, where plants, algae and plankton grew. The organisms went through their normal phase of photosynthesis, and overtime, when the plants died, they were buried by sand and rock. In theory, several layers of mud, sand, rock, plants and animal matter built up until the pressure and heat decomposed the matter and converted into fossil fuels.

Fossil fuels are the most common sources for electricity generation in the United States, it follows the same trend throughout the world. In the U.S., natural gas alone, generates 34 percent of the electricity used in the country. Natural gas is produced in natural gas and oil wells both on land and offshore. To be able to determine where natural gas can be found, geologists often use seismic surveys on land and in the ocean to identify the right places to drill wells. If a site seems auspicious, an exploratory well is drilled and tested to conclude whether or not the site is rich in natural gas. If the site is fit, developmental wells are drilled to extract natural gas. Although most of the natural gas extraction of the United States is done on the land, some wells are drilled offshore, in the ocean floors of the coast of the country with the majority of the extraction taking place in the Gulf of Mexico (U.S. Energy Information Administration 2018).

2.1 Natural Gas

There are three major types of pipelines that oversee the effective and efficient transportation of natural gas across the country, the gathering system, the transmission pipeline system and the distribution system. In the gathering system, the natural gas obtained from fracking, is used to transport it to the processing plant, from where the natural gas is separated from various hydrocarbons and fluid. Transmission pipelines system transport the processed natural gas thousands of miles from processing facilities across the country. Finally, the distribution pipeline system is in charge of distributing natural gas to homes and businesses through large distribution lines. The United States has about 305,000 miles of interstate and intrastate pipelines that transport natural gas all over the country (U.S. Energy Information Administration 2018).

In 2015, natural gas reached its peak in production in the country, where 65 percent of the natural gas generation is produced in the following five states:

- Texas (26%)
- Pennsylvania (18%)
- Oklahoma (9%)
- Wyoming (6%)
- Louisiana (6%)

There are multiple methods to produce energy from natural gas (U.S. Energy Information Administration 2017). Perhaps, the most common is a steam generation unit, which consists in burning the gas in a boiler where water is heated, and the steam produced makes a turbine rotate to generate electricity. The acquisition of natural gas and its consumption influence in the alteration of the environment. When a site has been

declared fit for the extraction process, usually it is necessary to clear the area where the drilling is taking place, this causes disruption in the vegetation, wildlife, and water resources. Equally important, adding to the disruption of the drilling, the transportation of natural gas through the pipelines system, requires installing the needed infrastructure to meet the demand. To be able to construct a pipeline, the path must be clear, often leading to the removal of trees or bushes to create trenches to install the pipelines. In spite of some negativity from the localization, extraction, production and distribution of natural gas, there has been some advances in technology which makes it possible to discover natural reserves while drilling fewer wells, this way, the there is a positive impact by causing less disruption in the environment. Furthermore, there is ongoing research for new initiatives to be applied to reduce the adversity that involves natural gas.

2.2 Coal

Coal is considered as a non-renewable energy source because it takes millions of years to form. In the United States, coal is the source of about 30 percent of the electricity generated in the year 2016. Coal can be extracted in one of two ways, by *surface mining* and *underground mining*. Surface mining is used to obtain coal that is less than 200 feet underground. Miners use large machines to remove the topsoil and layers of rocks. Most of the coal obtain in the United States comes from surface mining simply because it is less expensive than underground mining. When retrieving the coal from several hundred feet underground, it is then referred as underground mining. In some cases, coal mines can be found deeper than 1,000 feet and it can extend for miles. The coal collected from mining is then sent to a plant to process it; removal of rocks, dirt, ash and sulfur and other

unwanted materials is done at the processing plant. After the coal has been cleansed, it is then transported to a power generating plant to develop energy.

Electricity generation from coal is analogous to the electricity generation from natural gas. Power plants generate steam by burning coal, the steam generated is used to turn turbines from which the rotary mechanical power generate electricity. In 2015, the average sales price of coal at the mine was $31.83 per ton, and in average, the delivered coal price was $42.48 per ton. The resulting difference from buying the coal and the transportation of it is 25 percent of the mined coal. In the same year, 71 percent of total US coal production is accounted to the following five states:

- Wyoming - 41.9%
- West Virginia - 10.7%
- Kentucky - 6.8%
- Illinois - 6.3%
- Pennsylvania - 5.6%

The usage of coal indicates a higher impact in the environment in other words, the production and the usage of coal affects the environment. For instance, in the US, large amounts of coal are extracted from the Appalachian Mountains in West Virginia and Kentucky. Extracting coal from the top of the mountain implies to use of explosives to remove the top of the mountain. Other that changing the landscape, streams of water get covered with rocks and dirt, causing the run-off water to contain pollutants that affect the wildlife. In addition, when electricity is produced from coal, several principal emissions results from coal combustion that contribute to acid rain, smog, haze and respiratory illnesses among other negative contributions. Taking into account all the negative

environmental effects the use of coal has, research is currently underway to find a more energy efficient method to use coal so less of it has to be burned. In addition, Acts such as The Clean Air Act and the Clear Water Act were passed, which require industries to curtail waste discharged into the air and water (U.S. Energy Information Administration 2017).

2.3 Nuclear Energy

Nuclear Energy is another source of electricity generation that is considered a Non-Renewable source. Nuclear Energy itself is a renewable energy source, but uranium, which is used in the power plant, is not. Uranium is a common metal found in rocks worldwide, as a matter of fact, it is about 100 times more common that silver. Although uranium is prevalent, nuclear power plants compel a certain kind of uranium known as U-235, which is relatively rare. Natural uranium is composed of two different isotopes, uranium-238(U-238) which accounts for 99.3 percent of the composition, while uranium-235 (U-235) is about 0.7 percent.

The preeminent reason why the latter is used for energy generation, is because under certain conditions, U-235's atoms split apart (fission) to create smaller atoms, creating high levels of heat, which is used to generate steam from heated water to spin large turbines that generate electricity. The United States generates more nuclear energy than any other country in the world (U.S. Energy Information Administration 2017). In addition, nuclear power plants generate about 20 percent of the U.S. electricity. The generation of electricity from nuclear power plants may be one of the most efficient ways to obtain electricity currently in the market. For instance, a single Uranium fuel pellet the

size of a pencil eraser, contains the same amount of energy as 17,000 cubic feet of natural gas, 1,780 pounds of coal or 149 gallons of oil (NEI).

As previously stated, nuclear energy produces GHG emissions during the fission process, but, according to the Nuclear Energy Institute, Nuclear Energy should be categorized as a sustainable method to generate electricity. Even though Nuclear Energy is one of the most efficient methods to acquire energy, if fail to follow the adequate procedures, it can be one of the most dangerous and potential disruptive ways to generate energy. The only recorder fatality while in a Nuclear Power Plant is from Chernobyl, Ukraine, in 1986, where twenty-eight exposed reactor staff and emergency workers died from radiation. People following the time of the accident, have been suffering from cancer and children in Belarus, Ukraine and Russia, undergo the effects of radiation through birth defects. According to experts, it is highly unlikely an incident with those dimensions as in Chernobyl will happen in the United States. Another concern the use of Nuclear Energy possesses is the nuclear waste it produces from the generation process, since it may last thousands of years for it to completely be removed from the face of the earth. Ongoing research have been done to find a solution to the problems of using nuclear energy.

3. RENEWABLE ENERGY IN THE UNITED STATES

Resources that are constantly replenishing are considered renewable sources. Countries like Costa Rica, Denmark, Iceland, Albania, Norway, Germany or Afghanistan acquire most of the energy used by their citizens from these sources. There are a number of sources that make up the renewable energy generation, for instance, you can create energy from solar, wind, hydropower, biomass, biofuels and geothermal sources. Today, the use of renewable energy sources is increasing, especially biofuel, solar and wind. According to the US Energy Information Administration, EIA, in 2016, about 10 percent of the total energy consumed in the United States was generated from renewable energy sources. In addition, data from the EIA shows that about 15 percent of the U.S. electricity generation was from renewable energy sources in 2016. ***Figure 5*** shows how the energy generation is distributed in the country by source, including Non-Renewable and Renewable sources.

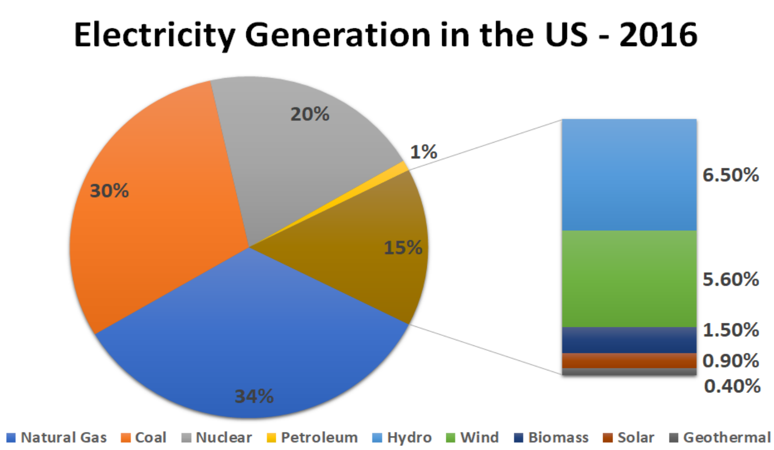

Figure 5: **US Electricity Generation**

The use of renewable sources has increased in the past years. With actions such as the 2015 Paris Agreement and numerous studies that suggest how to combat climate

change and potentially reduce the amount of Greenhouse Gas Emissions we contribute to the environment have strengthened the idea of using renewable energy as the main source for obtaining the required energy demand. This trend can be found by the

From the past fifteen years, the energy generating sector has seen a small shift from mainly using fossil fuels to generate electricity to practicing generation of energy from renewable sources. It is known that in the year 2000, only 90,000 MW were generated from renewable sources, and in the year 2015, the total energy generated from these sources was 194,000 MW. That is a 115 percent increase in the generation of electricity from renewable sources. The ***Figure 6*** shows what each state is currently doing to increase the generation from renewable sources. It is important to mention that science does not lie, there is a potential problem and people are taking hands into matter to create the needed change.

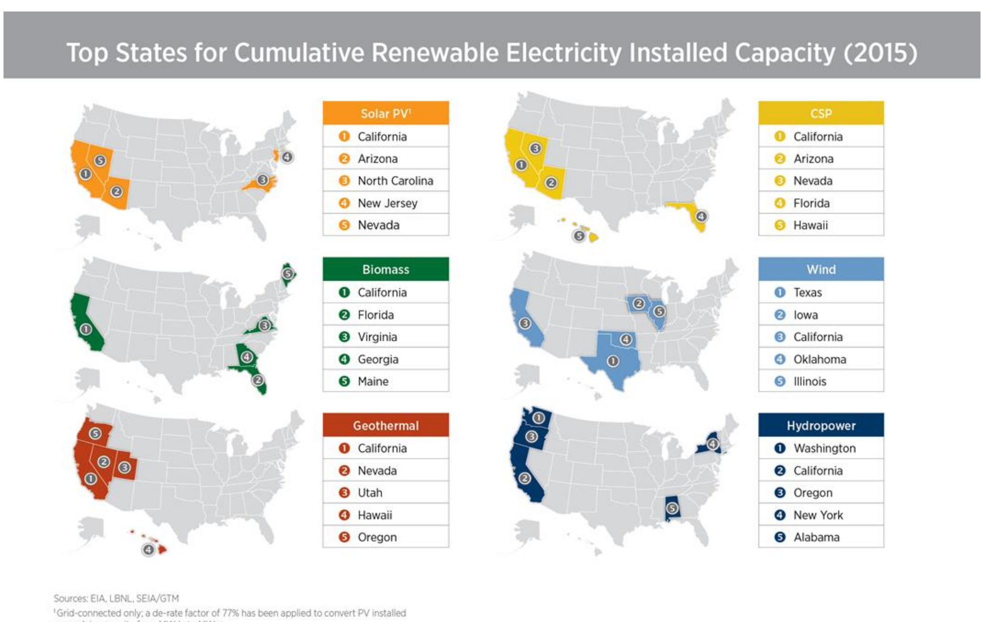

***Figure 6*: Renewable Energy Systems Installations in States**

3.1 Solar Energy

One of the most ancient sources humans have used for source of energy is solar. Solar radiation has been used since the 7th Century BC when people used a magnifying glass to concentrate the sun’s rays to start a fire. From that moment on, the way we utilize solar radiation has changed in many ways. Now, we use the energy from the sun to develop the capacity to have solar powered buildings, calculators, chargers and cars as well. There are different ways to produce energy from sunlight, the one which most people think about when talking about solar energy, is by using photovoltaic cells (PV) and the other is concentrating solar thermal power plants. A photovoltaic (PV) cell is used to convert sunlight into electricity; depending in the cell size along with the amount of solar radiation is what determines the total amount of power generated. In the same fashion, the efficiency of a PV cell fluctuates by the type of semiconductor material and PV cell technology. Up until today, the efficiency of a commercial solar panel can go up to 22.2 percent (Energy Sage, 2018).

One of the greatest challenges of having an efficient system of solar panels, is the availability of the source: the solar radiation. Solar radiation is the radiant energy emitted by the sun and that energy is vital for the generation of electricity (India Environmental Portal, 2008). For a solar panel to work at its highest efficiency, several factors need to be present. In the world there are only a selected number of areas where having solar farms would be viable for electricity generation at a large scale and one of the main reasons is total solar radiation received throughout the year. The amount of solar radiation present at a location could be affected by seasonal factors, climate effects, and the atmosphere (Salameh, 2014). The way seasonal factors influence the amount of radiation

received is through the comparison of radiation received during the summer is not the same as the one during the winter. During winter season, daylight time is shorter than the time we receive sunlight during the summer. Climate effects include the cloudy or rainy days. When the sky is clear, direct or beam sunlight is collected, but with the inclusion of clouds, radiation is being received as diffused or scattered sunlight. This is important to notice, since concentrating solar power plants will fluctuate if there are scattered clouds in the environment. Similarly, the presence of the atmosphere creates a reflection, reducing the amount of direct or diffused radiation received. All these factors impact the capability of a system to generate electricity from solar source.

Photovoltaic cells generate direct current (DC), and most of the electricity delivered today is alternating current (AC), therefore, an inverter is needed in a solar energy generating system to convert the electricity developed to the appropriate state. Generating electricity through a solar thermal power system assimilates to the production of electricity with fossil fuels. Solar thermal power generation systems use two components, a mirror (reflector) and a receiver. The mirror will direct the sunlight into the receiver, where it will concentrate the sun’s energy. A typical solar thermal power generation system uses a heat-transfer fluid at the receiver, whence the concentrated sunlight is yielding enough heat to produce steam from the fluid. This steam is converted to mechanical energy by rotating the turbine which powers a generator to produce electricity.

Solar radiance is the radiant energy emitted by the Sun. To determine a value to the power emitted, the term irradiation is used. Following the definition of the term *Power*: the rate of doing work, measured in KW, or watts; similarly, irradiance is the radiant power per unit area, and it is measured in kW/m^2 or watts/m^2.

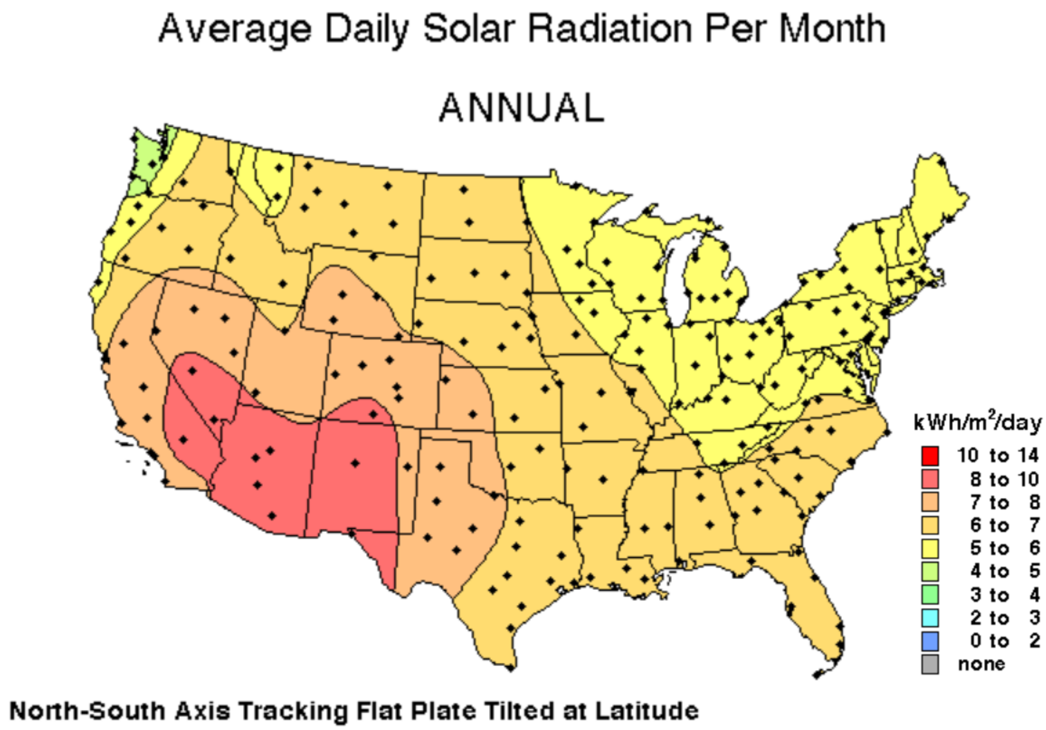

***Figure 7*: Average Daily Solar Radiation Per Month**

Additionally, to determine the radiation's capacity to perform work, or energy, insolation is used. Insolation is the radiant energy per unit area and its units are kWh/m^2. Solar insolation is used in the calculations that determine a solar panel's energy generation (FEFPA, 1998).

In the United States, the best area to produce solar energy is in the southwest of the country, as shown in ***Figure 7.*** States like California, Nevada, Utah, Arizona, New Mexico, Colorado and Texas, are known to be part of the Sunbelt States, partly because of the warmer climate they tend to experience in that region throughout a complete year.

Although, generating energy from sunlight might seem as concept easy to implement, it is important to note that only 1 percent of the total energy produced in the country comes from solar power generated electricity. Even though using solar generated energy does not contribute to the emissions of greenhouse gases, the main limitation for this kind of technology is the variability of the environment and the lack of sunlight depending in the season of the year. Contingent on your location, it is recommended to align the solar panels a certain way to maximize the availability of radiation.

There are a diverse number of orientations used to measure the total radiation an area is receiving. For instance, there is the Global Horizontal Irradiance (GHI), Diffuse Horizontal Irradiance (DHI), Direct Normal Irradiance (DNI), Average Tilt at Latitude (ATaL), Horizontal Flat Plate (HFP), or Two Axis Tracking Flat Plate (TATFP), to mention a few. Each orientation will give a different value. Let’s only take in consideration three, GHI, DNI and ATaL (National Renewable Energy Lab).

- GHI is one of the most common orientations and measurements used in scientific data. As its name says, the value of radiation is obtained by placing the panel horizontally flat to the ground.
- Similarly, DNI is also a popular orientation to measure radiance. In this case, the panel is always facing perpendicularly (or normal) to the sun rays that travel in a straight line from the sun.
- Setting a solar panel at a ATaL orientation means it is tilted with the direction towards the equator at an angle that is equal to the latitude of its present position. It is said that this orientation will yield a higher annual solar radiation.

The reality is that still in the year 2018, having a home where your sole or most of the electricity comes from the generation through solar panels is not an investment that you will see the economic benefits for ten to fifteen years. Research is still underway trying to identify the use of more efficient materials to generate more electricity and potentially use this technology in a higher scale across the country as well as more appealing and affordable approaches to reach the middle-class electricity users.

3.2 Wind Energy

A more efficient source with a higher capacity for energy generation than solar is the wind. The phenomenon of wind is induced by the divergence in the atmospheric pressure. When a variation in atmospheric pressure occur, air changes from the higher to lower pressure area, culminating in winds of various speeds. Humans have found a use for the wind as early as 5,000 BC, when people use it to drive boats along the Nile River. By the year 200 BC, windmills were used in Persia to grind grain. We have come a long way to now using wind to generate electricity (U.S. Energy Information Administration).

The first country in the world capable of using a wind turbine generator to generate electricity in was Denmark in 1890. Today, 40 percent of Denmark's supply comes from wind power, and as mentioned in their 2012 Energy Act, their goals is to reach 100 percent wind energy production dependency by the year 2050 (Denmark, 2015). In the United States, early colonists used windmills to grind wheat and corn, pump water and cut wood at sawmills. As the years passed, the use of wind became more popular across the citizens. During World War II, and individual called Palmer Cosslet Putnam alongside a manufacturing company of hydraulic turbines called the S. Morgan Smith Company,

developed the first wind turbine in the world that had the capacity of generating more than 1 MW of electricity. The wind turbine could endure winds of more than 115 miles per hour. This turbine was installed in Castleton, Vermont in 1941. By the year 1945, the turbine had to shut down due to a failure on a blade. During that period of time, fixing something made out of steel could elevate to exorbitant prices, making it unfeasible to repair the turbine (Technica Communications, 2016).

During the 1970's there was oil shortage in the country and some environmental concern; thanks to these events, the energy generation began creating a shift by investing in new technologies that will be more beneficial to the environment. Around the 1980's the Federal Government began to support the research and development projects through funding to lessen the cost of turbines. Moreover, during the decades of the 1990's and 2000's, the Federal Government introduced the granting of incentives for the usage of renewable energy sources as a part of their involvement to preserve the environment. The consumption of wind energy has seen a small but significant transformation in the current century. During the year 2000, only 1 percent of the energy generated in the country came from wind production. However, in the year 2016, 6 percent of the total energy produced was from the wind (U.S. Energy Information Administration 2017).

For electricity generation through wind, it is essential to have a wind turbine. A wind turbine is made up from different components, such as the blades, rotor, generator, controller, yaw drive and the tower. Turbines are made up of three blades that are connected to a rotor. The energy in the wind, called Kinetic energy, turns to the turbine blades around the rotor, creating mechanical energy. The rotor, which is connected to the main shaft, turns inside the generator housing. Here, a magnetic rotor spins inside loops

of copper wire that causes electrons inside the copper wire to flow, creating electrical energy. A step-up transformer increases the electrical generation from 690 V to 3400 V. The electricity generated now flows down the tower towards underground cables that are directed to a substation. Afterwards, the electricity is taken into a transmission line where it is delivered to different electrical grids to power houses and businesses for our daily activities. It also contains an anemometer, this device recognizes the direction of the wind, this way the turbine will rotate accordingly facing towards the normal or perpendicular to the direction of the wind to optimize the generating capacity (U.S. Department of Energy).

Meticulous planning is required to identify possible sites that contain the basic capabilities to install a wind farm. For instance, an ideal location would be someplace where encompasses high wind speeds, such as areas with long altitude, mountain gaps that funnel and intensify the wind speed, and offshore, to mention a few. Wind speeds varies throughout the country the same way it differs at a certain location from season to season. In some areas, the wind reaches a higher speed during the winter, while others have great speeds throughout the year except during the winter. In 2016, forty states had utility-scale wind power projects. Currently, five states contribute to 55 percent of wind power electricity generation and they have the following energy capacity generation (U.S. Energy Information Administration 2017).:

- Texas (20,321 MW)
- Iowa (6,917 MW)
- Oklahoma (6,645 MW)
- California (5,662 MW)
- Kansas (4,451 MW)

It is important to note that turbines are installed in various blade and towers sizes. In the United States, the average size of a wind turbine used for high scale power generation is 280 ft tall and this number has only been increasing for the past 10 years.

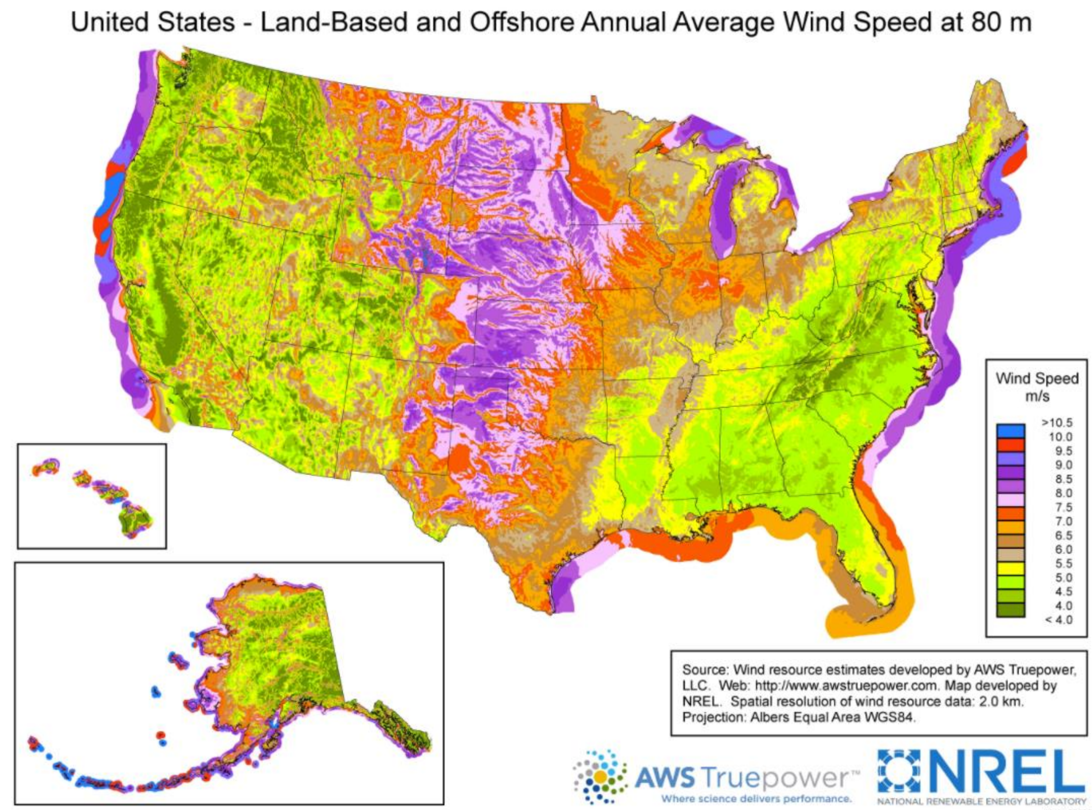

***Figure 8*: Land and Offshore Wind Speed at 80 meters**

According to data collected from EIA, there is a correlation with the power generated and the size of the blades. The larger the blade, the higher the output yield. With the use of higher turbines, the capacity of power generation also increases. In the year 2016, turbines that are part of the offshore Block Island Wind Farm in Rhode Island have a 6 MW power generation capacity. Onshore, the turbines with the greatest capacity are installed in Texas, with a capacity of 4 MW each (U.S. Energy Information Administration).

Though it is important to address, there has been a significant increase of wind power capacity generation since the year 2000. According to studies by the National Renewable Energy Laboratory, the United States has the wind capacity to generate close to 37,000,000 gigawatt-hours (GWh) annually, which is more than nine times the total US energy consumption using only the onshore wind resources. The study suggests that with the implementation of new technology, reaching those numbers will be feasible (National Renewable Energy Lab).

Offshore wind power generation has not been implemented in high scales in the country. Nevertheless, Rhode Island began the first offshore wind power project in the US in 2016 called the Block Island Wind Farm and it has a capacity of generating up to 30 MW. It is located 3.8 miles from Block Island, Rhode Island off the Atlantic Ocean. To this day, there are several other projects like the Block Island Wind Farm still in the planning stages. Wind is an emission free source of energy, it reduces in large scale the air pollution and carbon dioxide emissions, or pollutants that may affect the water (U.S. Energy Information Administration 2015). Despite all of the great advantages of using wind energy, this source is still far from becoming the main origin for electricity generation in the country.

3.3 Hydroelectric Power Generation

Another great source for clean energy is water. The usage of water for electricity generation has been one of the most efficient ways that have ever been used. In addition, it is the largest renewable energy source in the United States. To be able to create electricity from water is called hydroelectric power or hydropower. Now, let’s go back and consider what factors are needed to have a suitable territory for this to be feasible. To

generate power from water, you need a region where the flow of water is rich or possible to achieve. It is important to understand the water cycle, since the amount of precipitation will determine how much water is available to flow in rivers and streams to produce hydroelectric power.

Hydroelectric power generation is performed in a hydroelectric dam. A dam is a structure built across a river with a large reservoir. The idea of hydroelectric power generation is to create electricity from the flow of the water. To achieve an appropriate water flow velocity, a drop-in elevation is required, this way, water, with the force of gravity, will reach a higher velocity. Near the bottom of the dam wall, there is an intake (opening), where water will now flow through a penstock (which has a drop elevation) that will take the water to the turbine. The force of the flow will make the turbine spin, which then turns a metal shaft in an electric generator producing electricity.

In 2016, the United States generated about 266 million megawatt hours from hydroelectric power generation, which is about 6.5 percent share of the country's total energy generated (TVA). Let's take in consideration that to create energy from water, large amounts of water flow are needed, in addition, weather is uncontrollable and there has been significant changes in the weather's behavior. In the same year, the following five states generated 67 percent of the country's hydroelectric power generation:

- Washington - 29%
- Oregon - 13%
- California - 11%
- New York - 10%
- Montana - 4%

Perhaps the hydroelectric power generation does not pollute the environment with greenhouse gas emissions, but, in fact, it does have a negative impact in the environment. From all the dams in the country only a few were specifically built to have hydroelectric generators, the rest, its main purpose was to control flood, municipal water supply and irrigation water. Dams affect the ecosystem in several ways. Possibly one of the most significant is the obstruction of fish migration. Many species of fish, such as salmon and shad are used for commercial purposes, and they are being significantly affected while migrating by the obstruction of their path by dams. Furthermore, the use of hydropower turbines injures and kill significant number of fish that pass through the turbine. In addition, the process to create these dams have a negative impact in the environment. As previously stated, the act of generating electricity from a dam, does not emit any pollutants to the environment, but the machines used for their construction, do emit pollutants to the air and to the water as well. An investigation made by the Department of Energy in 2012, estimated that, if the non-powered dams in the country were modified with hydroelectricity generators, a potential increase of 12,000 megawatts could be reached. In addition to generating electricity from water dams, the state of Oregon has implemented a system which uses the water that runs off the streets into the sewers and using rotational blades, they generate enough electricity for at least 150 homes per year. Although there are a lot of advantages in hydroelectric generation, there are a couple of negative outcomes to consider. Scientists are developing new hydraulic turbines to decrease the negative impact in the ecosystem (Popular Science, 2015).

3.4 Biomass

In addition to the most known sources of renewable energy, solar, wind, and water, we can also get energy from biomass. The term biomass refers to plant material and animal waste; its use dates back to the time period when humans uncovered the mystery of fire (Society of Irish Foresters). Plant material and animal waste are considered to be renewable energy sources because they can regrow over a short period of time, compared to fossil fuels which take millions of years to form. Plants absorb energy from the sun through photosynthesis, when the biomass is burned, its chemical energy stored is released as heat. There are several types of biomass such as wood, landfill gas, alcohol fuels, crops, and garbage.

Wood is one of the most ancient ways to create energy ever used in history up until the mid-1800's. Across the world, particularly in developing countries, wood continues to be a fundamental source of energy. Among the various uses, wood has, it is mainly used for cooking, heat, and light. Additionally, power plants across the United States use wood and wood-based products as a substitution of other fuels, since these significantly reduce the GHG emissions and minimizes the cost of producing energy.

Garbage is one of the methods used to produce biomass through municipal solid waste (MSW). Some of the different types of waste found in MSW is food waste, paper, plastics, metals, wood, glass among others. In the country, there are 71 power plants who use some of the garbage to produce electricity. The most used products are paper, cardboard, food waste, grass clippings, leaves, wood and leather products. The burning of these materials at the plants make up about 14 billion of kilowatt-hours of electricity.

Using this method, other than generating cleaner energy, it also reduces the amount of waste material found in landfills.

Energy can also be produced from the waste found in landfills. This waste can produce a bacteria called anaerobic bacteria which can live in places that lack oxygen, decompose the organic waste and produce a gas called biogas. What is interesting about this biogas is that it contains methane, which is the property that allows it to become a source of energy. Several numbers of landfills in the country collect biogas, treat it and sell the methane. Similarly, the same bacteria are found in animal dung. Farmers collect the manure, treat it and sell the biogas. The methane found in the biogas is commonly used for heating and electricity generation.

The use of biomass as a source for energy has its positive and negative effects. For instance, plants contain CO2 from photosynthesis, and while burning they might be less harmful to the environment, they are still releasing carbon dioxide. In addition to biomass, if the burning of wood and municipal solid waste is taken into consideration, it is found that they also release some greenhouse gases as well as the contribution of air pollution and chemicals discharge onto the environment.

4. METAHEURISTIC OPTIMIZATION

Various combinatorial optimization problems are complicated to solve using a heuristic algorithm. These types of problems are referred to as NP-hard problems, due to its computational complexity, which this could be an exponential computation time. That is why the inclusion of new algorithms that, will not necessarily provide an optimal solution, but rather present the best solution as possible have been developed. This kind of algorithms are part of the family of metaheuristic algorithms. The word Heuristic means “to find”, and essentially when using a heuristic algorithm, the user is looking for a solution that will allow to perform as what he wanted (Bianchi, et al, 2008). In Metaheuristic, the suffix “meta” means “beyond, in an upper level”. Metaheuristic algorithms refines a heuristic algorithm and they are used to find a high-quality solution to hard problems in a reasonable time (Dorigo, et al, 2004).

4.1 Ant Colony Optimization

Ant Colony Optimization (ACO) is one of the algorithms used for optimization. ACO was first introduced by Marco Dorigo in the early 1990’s. The idea behind this technique of optimization was developed by the way the ants communicate to find the shortest path to a food source from their nest. Ants communicate with each other via sounds, touch and by pheromones. The pheromone left by one ant can be easily detected by the sensitive antennae of another ant. When trying to get to a specific place, each ant will go their own route, leaving off pheromones on their way through. The pheromone will evaporate at some point before another ant, or the same ant comes back through the same route. (Dorigo, et al, 2004) (Dorigo, et al, 2006). The ant that finds the shortest path to their destination will return to its colony through its initial route and the trail’s pheromone

will increase. The trail that has the highest level of pheromones will be the most attractive to the rest of the colony. In this case, the ants utilize pheromone to optimize their paths by finding the fastest route.

In ACO, the program imitates the actions of the ants, where the artificial ants are attracted by the artificial pheromone trail. The way the algorithm works is by probability. It is important to show the different variables the algorithms needs in order to perform and complete the desired calculations. ACO is a stochastic constructive procedure which is in constant construction to find the optimal solution. The following is a formal characterization of the representation the ants use and policy they implement: (Dorigo, et al, 2004). In a minimization problem (*S*; *f* ;Ω), where S is the set of candidate solutions, *f* is the objective function which assigns an objective function (cost) value *f*(s,t) to each candidate solution $s \in S$ and Ω(*t*) is a set of constraints. The variable *t* under the objective function and the constraints indicate they are dependent on time. The intention is to find a globally optimal feasible solution with an object of minimal cost value. The following formula helps the ant decide which path it should take:

$$P_{ij} = \frac{\tau_{ij}}{\sum \tau_{ij}} \tag{1}$$

Where $P_{ij}$is the path chosen, $\tau_{ij}$is the artificial pheromone value for each of the links available.

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \Delta\tau_{ij} \tag{2}$$

Where the ρstands for the rate of evaporation of the pheromone and the value of $\Delta\tau_{ij}$can be obtained by the following equation:

$$\Delta\tau_{ij} = \frac{1}{L_{ij}} \qquad (3)$$

In this case, L_{ij}stands for the cost of pheromone evaporation.

The artificial pheromone used in the algorithm is used as a "distributed, numerical information" that the ants utilize to define create various solutions to a given path, and by every iteration done the ants are approaching if not an optimal solution, a solution close to the optimal (Dorigo, et al). This method can be used to solve discrete optimization algorithms, where you need to find an optimal solution from a number of possibilities.

ACO - Algorithm pseudo-code:

while *termination condition not met* ***do***
        ScheduleActivities
                ConstructAntsSolutions()
                UpdatePheromones()
                DeamonActions() {Optional}
        end ScheduleActivities
end while

The Ant Colony Optimization algorithm is an iterative algorithm, in which it is controlled by the while function, and as long as the constraints for the function are true, the algorithm will iterate until it has met the initial conditions assigned. The ACO algorithm follows three different procedures: *ConstructAntsSolutions, UpdatePheromones* and *DeamonActions*, all of which are represented in the algorithm (Dorigo, et al, 2004).

ConstructAntsSolutions refers to the movement of ants who are building solutions by visiting states of the considered problem while moving through different nodes from the problem's constructed graph Gc. They stochastically move around the Gc by sensing the pheromone intensity and heuristic information. While each ant is creating its own solution (complete or partial), depending on its quality they will evaluate the

amount of pheromones deposited in the ***UpdatePheromones*** procedure. (Dorigo, et al, 2004) (Blum, 2005)

UpdatePheromones refers to the process in which the pheromone that was left by the ants while traveling either loses its intensity and it decreases over time or the path was used by multiple ants or one ant used the path and created a very good solution, then the pheromone intensity will increase. This process also offers a useful method of ***forgetting***, it avoids a rapid convergence of the algorithm toward a specific region, making the route less attractive for the upcoming ants in future iterations obliging the ants to find a new path (Dorigo, et al, 2004) (Blum, 2005).

DeamonActions is a part of the algorithm that can be omitted if it is not necessary for the operation. ***DaemonActions*** are used to "*implement centralized actions which cannot be performed by single ants".* This part of the algorithm oversees the iterations and notices the most feasible paths available. As the completion of new iteration passes by, ***DaemonActions*** will add some pheromone to the paths that have the best solution, increasing its demand (Dorigo, et al, 2004).

4.2 Particle Swarm Optimization

Another evolutionary computational algorithm that has been used in recent years is the Particle Swarm Optimization (PSO) algorithm. The technique was developed by Kennedy and Eberhart in 1995. The idea behind PSO was inspired by social behavior and dynamics of bird and fish flock. The algorithm is based from different studies where can be found the choreography of the flocks, for instance, bird flocks, synchronously flying

they are going to a same direction, but often change directions, they scatter and after a short period of time they regroup.

Birds travel in flocks; there are many reasons for which they have such behavior, such as giving a perspective of being less vulnerable to predators, but the main reason to why birds fly in flocks is to find food and the fastest path to get to it. Just as birds, fishes form schools which swimming together as a large group confuse predators and are less likely to be attacked.

The initial purpose of the algorithm is to simulate the unpredictable choreography of the flock and school. Depending on the result from each iteration, some modifications could be implemented, like the nearest-neighbor velocity matching, eliminate ancillary variables, or incorporate multidimensional search and acceleration by distance. The sole purpose for the adjustments is to optimize the upcoming iteration. The main steps that are used in the algorithm are listed in the pseudo-code below (Kennedy, et al, 2001):

PSO – Algorithm Pseudo-Code:

for *each particle*
    Initialize particle
end for
Do *for each particle*
        Evaluate fitness value
            if the fitness value is better than the best fitness value (pBest) in history,
            set current value as the new pBest.
end do
(Choose the particle with the best fitness value of all the particles as the gBest)
for *each particle*
    calculate particle velocity according to previous equations
    update particle position according to previous equations
end *for*

This pseudo code is best described in the Flowchart below:

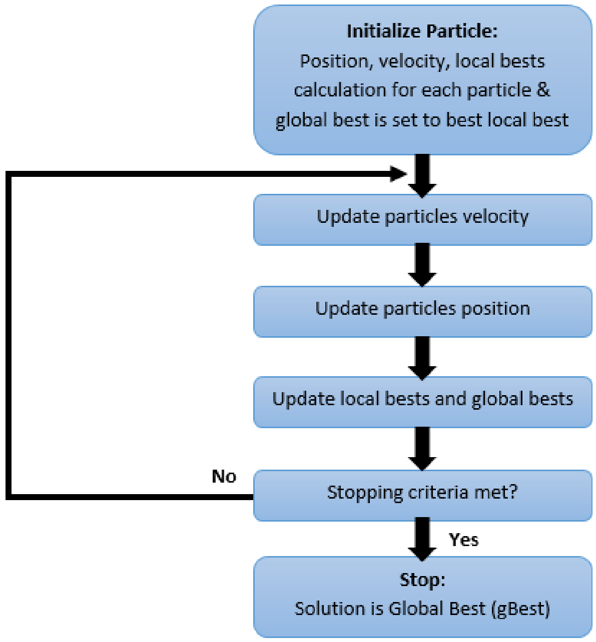

***Figure 9*: PSO Flow chart**

In the algorithm, each bird is considered a particle rather than an actual bird. While the PSO algorithm is performing the **Initialization** phase, a population of particles is given a random position and *X* and *Y* velocities (Kennedy, et al) From the initial conditions randomly provided, a calculation of the local best (*pBest*) is performed to every particle in the population. The particle with the best p*Best*, is assigned the term global best (*gBest*). Once the initial *gBest* particle has been found, then the algorithm will update the particle's velocities, position and a new *pBest* and *gBest* will be assigned to the population. The algorithm will stop running after certain number of iterations have been run (the user can define the number of iterations needed/wanted), or an optimal solution has been found (let's remember this is a metaheuristic algorithm, which not necessarily will give us the ideal optimal solution to a NP-hard problem).

In the PSO algorithm the program is being running with a set of birds randomly placed in a position and X and Y velocities. After an iteration a loop determined the birds that are close to each other, and one of the birds will end up having the same X and Y velocity than the other bird. After certain iterations the majority of the flock is sharing the same X and Y velocities. To change this, a “feature” called craziness is added to the code, where it randomly introduces a new set of X and Y velocities. This allows some variations in the code. It is important to understand that in this part of the code, the birds are flying without a given direction, they just know their starting positions and with the “craziness” they are able to make variation in their positions and velocities.

To be able to visualize how the flock or the school is updated while traveling within the algorithm, ***Figure 16***, shows how each particle changes position and velocity according to previous results from its *pBest* and the *gBest* of the population (Wang et al, 2016)

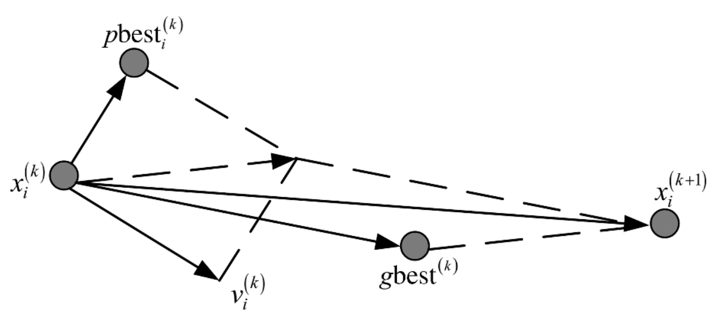

***Figure 10*: PSO Visualization**

Where:

$v_i^{(k)}$: is the velocity of the i^{th} particle in the k^{th} iteration.

$x_i^{(k)}$:is the position of the i^{th} particle in the k^{th} iteration.

$x_i^{(k+1)}$: is the position of the i^{th} particle in the next iteration after the k^{th} iteration.

4.3 Harmony Search Optimization

While listening to music, there are certain notes, pitch, beats and combinations that our brain consider to be aesthetic and pleasant for us. Following this ideology, an optimization algorithm was introduced, Harmony Search Optimization (HSO). HSO was developed by Dr. Zong Woo Geem during the year 2001. The algorithm was inspired by the musical process of searching for a perfect state of harmony (Zong, et al, 2001). For instance, the algorithm was developed using as an example a music improvisation of a Jazz trio. Each of the members of the trio use a different instrument than the other. They all start playing different notes until they reach the desired combined harmony from the three instruments (Zong, et al, 2001). Similarly, this algorithm randomly inputs values for different variables until the appropriate desired output has been reached.

This idea of finding a better state of harmony was derived based on musician's performances, such a trio jazz improvisation. There are three rules in which a musician improvises one pitch:

- Play any pitch from the musician's memory.
- Play an adjacent pitch of one pitch from the musician's memory.
- Play a totally random pitch from the possible sound range.

Each musician is randomly changing its pitch until all three of them hit a specific note and are within the desired state of harmony, the experience is stored in each player's

memory making the possibility of creating a good harmony higher for future iterations. The Harmony Search Meta-Heuristic Algorithm follows these 5 steps:

- Initialize the optimization problem and algorithm parameters.
- Initialize the harmony memory (HM).
- Improvise a new Harmony Memory from the HM.
- Update the HM.
- Repeat Steps 3 and 4 until the termination criterion is satisfied.

The following is the pseudo code of the algorithm followed by the flow chart shows the path in which the described steps will flow (Mahdavi, et al, 2007).

HS – Algorithm Pseudo-code (Yang):

begin
    Objective function f(x), $x=(x_1,x_2, \ldots,x_d)^T$
    Generate initial harmonics (real number arrays)
    Define pitch adjusting rate (r_{pa}*), pitch limits and bandwidth*
    Define harmony memory accepting rate (r_{accept}*)*
    while *(t<Max number of iterations)*
        Generate new harmonics by accepting best harmonics
        Adjust pitch to get new harmonics (solutions)
        if *(rand>* r_{accept}*) choose an existing harmonic randomly*
        else if *(rand>*r_{pa}*), adjust the pitch randomly within limits*
        else *generate new harmonics via randomization*
        end if
        Accept the new harmonics (solutions) if better
    end while
    Find the current best solutions
    end

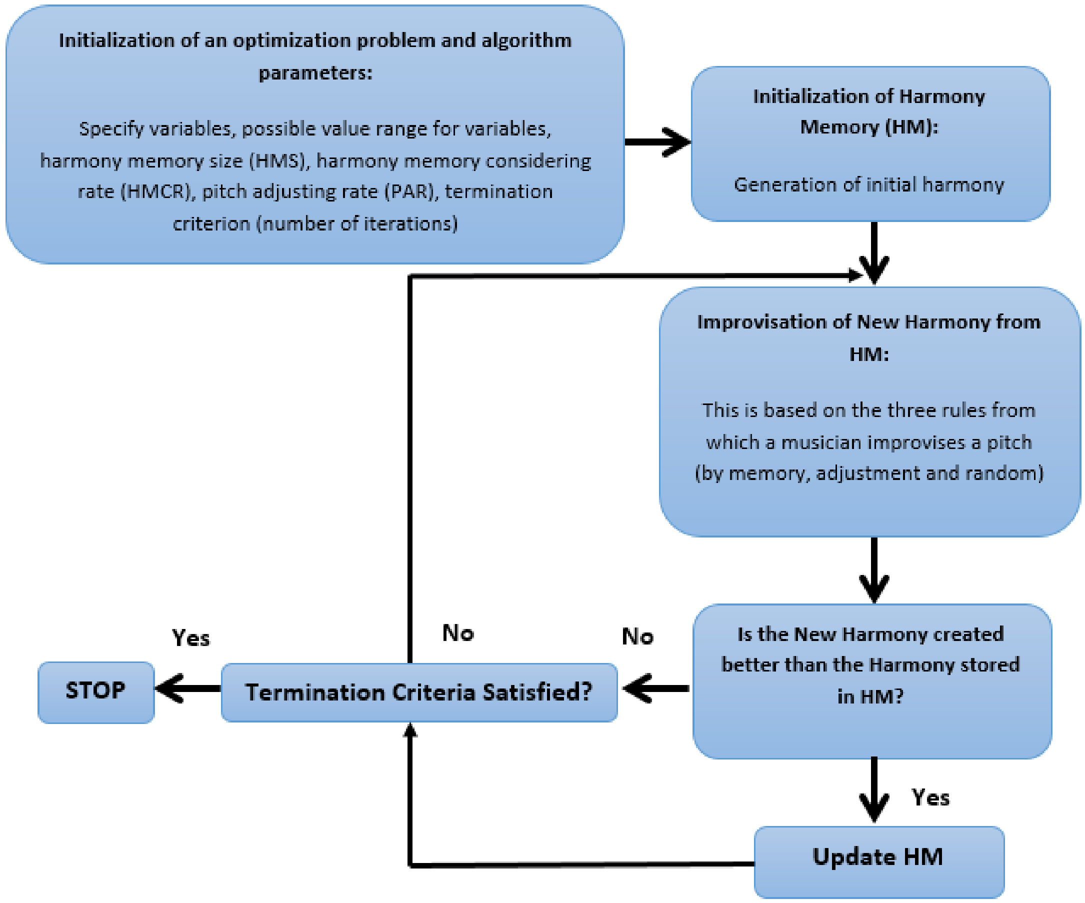

***Figure 11*: Harmony Search Flow chart**

Going over the flow chart above, Step 1 consists in defining the variables in order to minimize the objective function. Assigning range of values to each of the variables, defining a harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR) and the termination criterion (number of iterations). Step 2 is the initialization of harmony memory. In this step, a random generated solution is created in the Harmony Memory matrix. In Step 3 consists in improvising a new harmony from the already defined Harmony Memory. The new randomly improvised harmony is based on memory considerations, pitch adjustment and randomization. In Step 4, the algorithm

will decide whether to update the newly created randomly improvised harmony or what was stored before it. If the newly created randomly improvised harmony has a better output than the harmony previously used, then the memory will store the newly created harmony in the Harmony Memory. Finally, Step 5 consists in repeating Steps 3 & 4 until the termination criteria is has been met. To decide whether the termination criteria has been met, it is necessary to determine how many iterations the user wants to have for the code and also, since this is a heuristic algorithm, there will not be an optimal solution, therefore, an output value that is the closest to the expected optimal solution will be the best answer for the algorithm.

4.4 Tabu Search

Tabu Search (TS) is another algorithm used to find a good solution to a combinatorial optimization problem (Alain, 1995). Tabu Search was first introduced by Glover in 1986 with an input from Hansen in 1989. Unlike previous examples, this is not a nature inspired algorithm, but it has been proven to work just as well as any other. TS's main purpose is to find a global optimum solution while comparing local optimum solutions with neighbor optimal solutions for a predetermined number of iterations until the termination criteria input by the user has been met. Tabu Search also incorporates an adaptive memory and responsive exploration, this is used in order to qualify the algorithm as an intelligent form of finding a solution (Glover, 1995).

Tabu Search is known to be a more sophisticated and improved form of local search algorithm. To better understand how a local search algorithm works, the simplest and known example of a local search algorithm is Hill Climbing. In Hill Climbing, the user assigns an initial solution, the algorithm then starts creating neighbor solutions and

compares the neighbor solutions with the first assigned initial solution. If any of the neighbor solutions is better than the initial solution, then the current solution will be updated for the solution found. The process will be repeated until *n* number of iterations the user had predefined or it can also finish once the current solution is better than all of the neighbor solutions, also called a local optimum. Similarly, Tabu Search utilizes the main idea behind Hill Climbing, but instead of culminating the search once a local optimal is found, it uses these three main features: best improvement, tabu lists and aspirations criteria.

Using ***Best Improvement*** allows to change the current solution after each iteration by the best neighbor solution, even if this is not better than the current solution. Doing this will prevent having the problem of being stuck with the *local optimal* solution Hill Climbing uses, because selecting the local optimal might be the best in that iteration, but you do not give any opportunity to improve the solution. At the same time, with *Best Improvement* it is prohibited to visit a solution that it had already been selected as a current solution. Each time a solution is selected, a list is created, called ***Tabu List***, where all selected solutions after each iteration are stored. The last of the three main attributes is ***Aspiration Criteria***. With *Tabu Search* forbidding the algorithm to visit already selected solutions may be preventing to find new solutions with any combination of the solutions already visited. To prevent this, *Aspiration Criteria* is proposed in the algorithm. It will require a solution to be better than the best solution found in the algorithm. To better understand how Tabu Search works, below there is its flowchart:

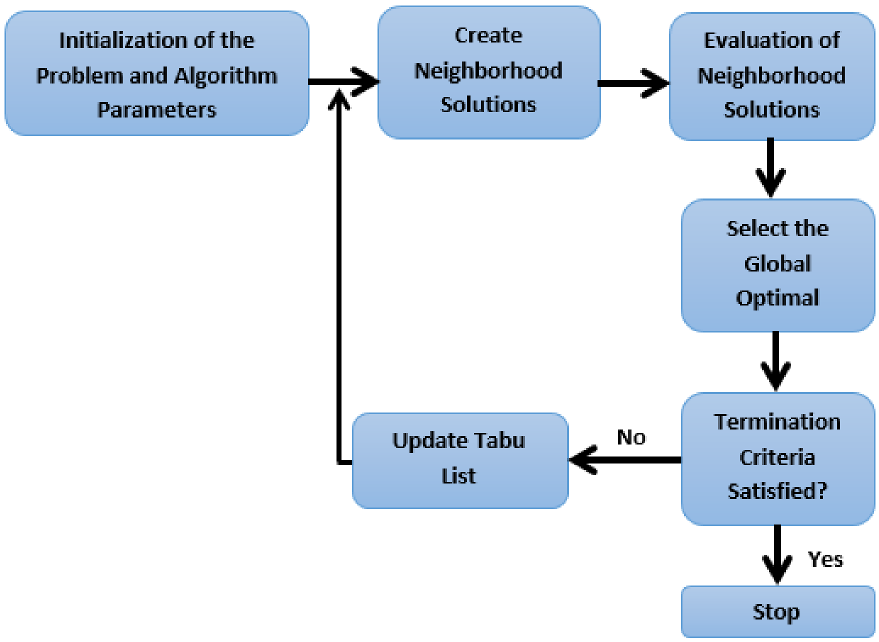

***Figure 12*: Tabu Search Flow chart**

Similarly, the main steps used in Tabu Search are listed in the following pseudo-code:

TS – Algorithm Pseudo-code:

Begin
Generate a starting current solution x
Initialize the tabu lists
for** iteration k = 1,2… **do
Set $A(x,k) = \{y \in S(x) \backslash T(x,k) \cup T(x,k)\}$
Set x = argmin $_{y \in A(x,k)}$*G(y)*
Update the tabu lists
end for
end

Where the *x* and *y* are feasible solutions to the problem. $A(x,k)$ is the set of solutions from which the current solution is chosen at iteration *k*. *S(x)* is the set of neighbors of *x*. Similarly, $T(x,k)$ is the set of tabu moves at iteration *k*. And finally, $T(x,k)$ represents the tabu moves satisfying an aspiration criterion.

4.5 Artificial Bee Colony Optimization

As from the different algorithms that had already been discussed, it is important to note that an important number of them are related to the way animals interact with each other to obtain the fastest route to a food source or to prevent an encounter or an attack from predators, similarly used in engineering or other technological practices to solve combinatorial and numeric optimization problems. Another swarm intelligent related algorithm has been used in the resent past years: **Artificial Bee Colony Optimization (ABC)**. The algorithm was first developed and introduced by Dervis Karaboga in the year of 2005 (Karaboga, 2005). As Karaboga has described his algorithm, it is known that the idea behind ABC was found by a research done by Valery Tereshko and the foraging behavior of a honeybee colony based on reaction – diffusion equations (Tereshko, 2002). The ABC algorithm imitates the behavior of a honeybee colony, where the three main components of Tereshko's model are (Karaboga, 2009)

- Food Sources
    - Where the forager bee evaluates different variables directly related with the food source such as the closeness to the hive, taste of its nectar, richness of energy, and how complicated is it to extract the energy from the food source.
- Employed Foragers
    - An employed forager is located at a specific food source location, where it acts as the messenger between the bees extracting all the benefits of the food and the bees waiting in the hive. An employed forager carries

information pertaining to the food source, such as distance from the hive, the direction and the profitability of the food source.

- Unemployed Foragers
    - An unemployed forager is a bee who is looking for a food source to *exploit*. The unemployed bee may be looking for a food source in the environment by random means, also called scouts, or it can be using information given by an employed forager, these bees are also known as onlookers.

What makes a hive of bees to keep on growing and function properly is the exchange of information within each other. The information mainly pertains in the quality of the food source, mainly specifying the distance, taste, richness etc. All this information is being exchanged in something called the *Dance Floor*; in this area the employed bees perform a waggle dance where the onlooker bees are awaiting for information of a presumable good food source. The dance performed by the employed bees, the waggle dance, solely depends on the profitability of the food source, meaning that, if the food source is of an excellent quality, then the higher the possibility the employed bee will share the information with her onlooker bee-mates (Tereshko, 2005).

From the research done by Karabago, he then later introduced Artificial Bee Colony algorithm, taking as the backbone of his work the findings previously introduce by Tereshko. In ABC, the position of a food source is representing as a possible solution, and the nectar amount of a food source represents the quality, also called the fitness, of the associated solution (food source). Also, it is determined that the number of food sources, or solutions, is equal to the number of employed bees, since only one employed

bee is associated with one solution (Karaboga, 2009). Karabago's Artificial Bee Colony algorithm pseudocode is shown below:

ABC– Algorithm Pseudo-code (Karaboga, 2012):

Initialization Phase
REPEAT
    Employed Bees Phase
    Onlooker Bees Phase
    Scout Bees Phase
    Memorize the best solution achieved so far
UNTIL (Cycle = Maximum Cycle Number or a Maximum CPU time)

In the *initialization* phase, the user defines the total number of food sources (solutions), the scout bees and control parameters. While at the *employed bee phase*, the artificial employed bees search for food sources richer in nectar within their memory range; once they have found one, they evaluate the food source quality. The bee will perform version of Genetic algorithm, creating new offspring and comparing their fitness within each other. Once done with the comparison, the employed bees reach out to the onlooker bees by waggle dancing in the *dance floor* to share information about their findings. In the *onlooker phase*, the onlooker bee probabilistically choose their solution depending in the information provided by the employed bee. Once the onlooker has reached the food source, an offspring is created with a new solution and a comparison between each other's fitness is done performed. While in the employed bee phase, there might be some bee's whose dance will not attract any onlooker bees because their solution cannot be improved after certain number of iterations. This type of solutions will later be available to scout bees. During the *Scout Bee* phase, the bee has the duty to randomly search for a new solution. These steps will continue running until a termination criterion has been met. Typically, a termination criterion for this kind of algorithm is

predetermined by the user and it is commonly defined as to the number of iterations performed to find the best set of solutions or the desired solution.

4.6 Simulated Annealing

In the year of 1983, Kirkpatrick proposed the Simulated Annealing algorithm which, by that time, it was one of the first ever proposed that will solve combinatorial problems (Kirkpatrick, 1983). Simulated Annealing is an adaptation of the Metropolis-Hasting algorithm, published by Metropolis in the year 1953 (Metropolis, 1953). The Simulated Annealing algorithm gets its inspiration of the metallurgical process of annealing, in which it involves heating of a material and slowly lowering the temperature, cooling the material (annealing) to increase the size of its crystals and reduce its defects, it is used to make the material as stronger as possible. One of the best characteristics the SA algorithms have is the ability to find a solution outside of the local best, in other words, the algorithm is capable of acquiring the global best of the problem. It is capable of doing so by:

$$p = exp\left(\frac{-\delta f}{T}\right) \tag{4}$$

Where δf is the increase in f (objective function) and T is a control parameter known as temperature in this algorithm (Busetti). The pseudocode of the Simulated Annealing algorithm is presented below:

SA – Algorithm Pseudo-code:

Initialize state x and temperature parameter T_1

for *iteration k = 1,2,…*
    select y randomly y from S(x)
    if $G(y) \leq G(x)$
    set x = y

else if $exp\left(\frac{G(x)-G(y)}{T_k}\right) \leq uniform[0\ ,1]$

set x = y

end

update T_k *to* T_{k+1}

end

Where:

- *S* is the search space and *G* is the objective function of the problem
- *X* and *y* are the feasible solutions from the search space *S*.
- T_1, T_2, T_n is a sequence of values assigned for the temperature parameter, it keeps updating depending on the solution of each iteration, most of the time, when updating the temperature, it tends to decrease as the algorithm progresses.

And the SA’s flowchart is shown as well:

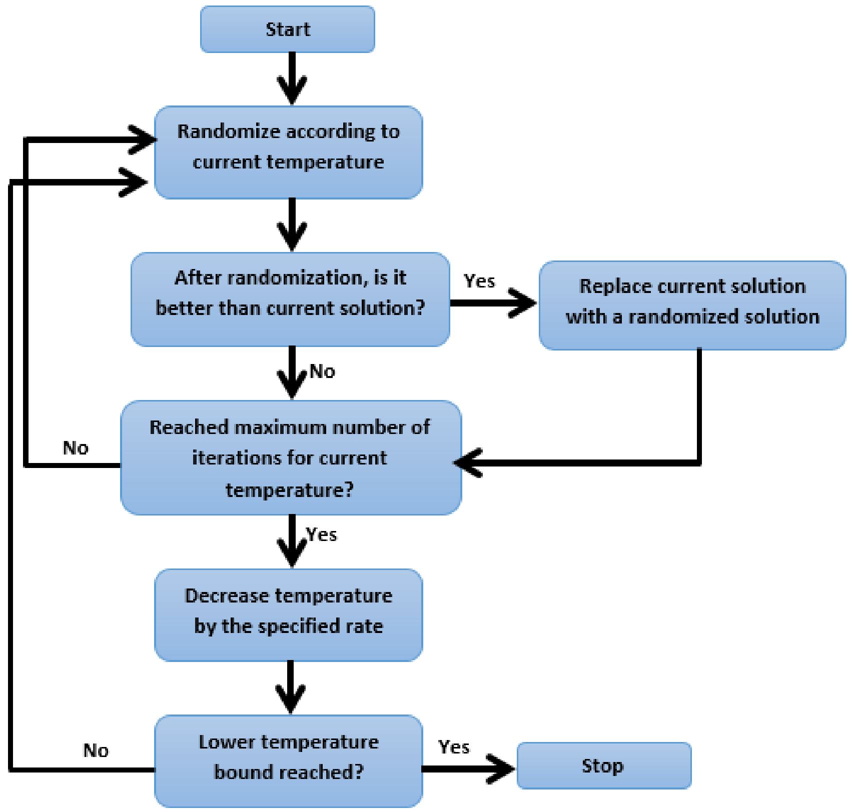

Figure 13: **Simulated Annealing Flowchart**

As it is illustrated in ***Figure 19***, the algorithm, at the START point, will generate a random solution utilizing the initial variables the user inputs. Then a randomization utilizing the current temperature will occur. If the newly created solution is better than the one current solution, then it will replace the current solution with the newly created, if the solution is not better that the current, then a new randomization will be performed according to the current temperature. This process will be repeated until a better solution is found. Afterwards, the algorithm will verify if the temperature decreased by the user specified rate. If the lower temperature bound has been reached then the algorithm will stop, if not, it will go back to the randomization according to its current temperature phase.

4.7 Genetic Algorithm

The Genetic Algorithm (GA) was first introduced by John Holland in the 1960s. Holland's original goal was to understand how the phenomenon of adaptation in nature works and to translate that natural adaptation mechanism and implement it in the computer world (Bunnag & Sun). Instead, his work has been used as an algorithm, inspired by the process of natural selection, that solves specific problems in optimization among other global applications.

The GA consists of a random population of *n* number of members, which the total number of members of the population is determined by the user. Each of the members in the population is represented as a chromosome. Each of these chromosomes are conformed by a string of genes, which carry a different characteristic of the chromosome and they can be represented in binary form, integer form, or value form.

- In the binary form, the string of genes takes the values of 0 and 1. If the gene has the value of 1, it implies that a particular component is active. In contrast, if it is 0, then it indicates it is inactive.

1	0	0	1	1	0	1	0

Figure 14: **Binary Encoding**

- Using the integer form for the creation of the population means there are more possibilities in a gene other than being active or inactive. In integer form, each gene may indicate a certain number of elements at a certain position, indicated at the placement inside the chromosome.

3	1	1	0	2	2	1	3

Figure 16: **Integer Encoding**

- Utilizing the value form is the most complicated of the three to introduce it in a GA. This way, a gene can take the value of a letter or a number.

A	C	A	B	C	A	B	B

Figure 15: **Value Encoding**

Figure 23 illustrates what a chromosome, genes and a set of solutions look like in the algorithm.

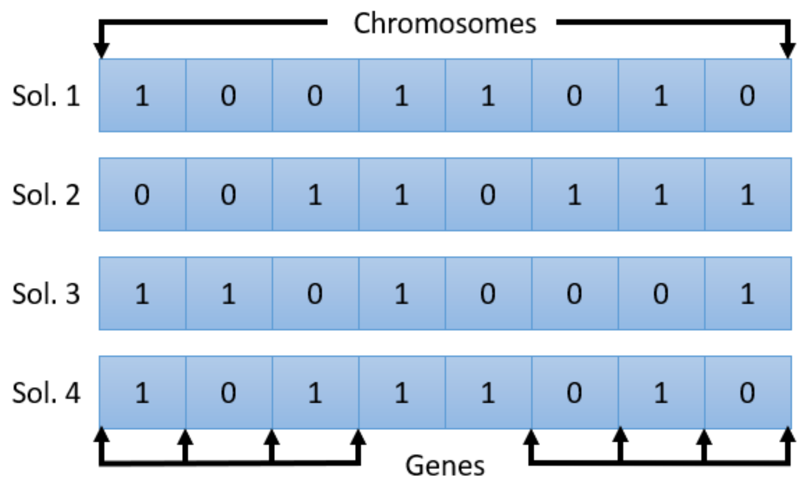

Figure 17: **Solution Representation**

Once all the initial solutions have been generated, then according to the parameters set, or the objective functions, the fitness of each solution is evaluated. There are several ways to evaluate the fitness value of the solutions: ranking selection, tournament selection or the roulette wheel selection.

- The ranking selection takes all the solutions and ranks them accordingly to the values obtained. A solution with a stronger value will rank at a higher level than the rest.
- In the tournament selection, the value of two random solutions are compared. Similarly, the solution with the stronger value has a better fitness value.
- Finally, in the roulette wheel selection, the solutions are arranged and grouped according to their fitness value. A solution with the better fitness value has a higher probability of being selected to move on to the next generation.

To avoid losing the best solutions, a defined percentage of elite solutions at each generation will move on to the next iteration. From the selected elite solutions, mutation and crossover is applied to create a new set of solutions. This process will continue until some termination criteria is met or an optimal solution is found. ***Figure 24*** shows the flowchart of the algorithm.

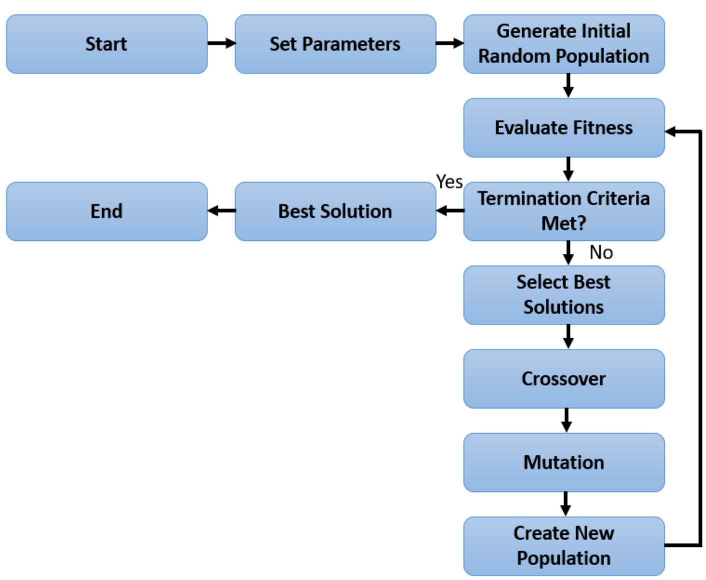

***Figure 18*: Genetic Algorithm Flow Chart**

The Genetic Algorithm is widely used in a variety number of applications. It goes from being used in the traveling salesman problem, climatology modeling and quality control to pop music record production and power generating modeling. It is a powerful tool, and it is the core of an optimization algorithm.

5. THE UNIVERSAL GENERATING FUNCTION

One of the earliest methods used to determine the reliability of a system was using the binary reliability theory. This theory assumed that the components of a system are made up from only two states, completely functioning or total failure. If the component was working, then the number one is used to denote it, otherwise, the number zero was assigned. Later, the Multi-State System (MSS) approach was introduced. It consists of a system with a finite number of performances rates, leaving behind the binary theory. In 1978, Barlow and Wu, were the first ones to evaluate a system as a multi-state system. In a multi-state system, there are four practical methods used to evaluate the reliability assessment:

- Structure Function Approach (Pourret et al, 1999) (Ushakov, 1994)
- Monte Carlo Simulation (Ramirez-Marquez & Coit, 2005) (Zio, Marella & Podofillini, 2007)
- Stochastic Processes “Markov” approach (Xue & Yang, 1995) (Lisnianski, 2007)
- Universal Generating Function (UGF) (Ushakov, 1986) (Levitin, 2004).

The Universal Generating Function (UGF), was first introduced by Igor Ushakov in 1986. The UGF is a powerful tool used to solve multi-state system optimization problems. The UGF consists of at least two independent random variables, v_1 and v_2 are two random variables with Pr{.}, their corresponding probability function:

$$Pr\{v_a = v_{ai}\} = p_{ai} \quad 1 \le i \le k_{ai} \qquad (5)$$

$$Pr\{v_b = v_{bj}\} = p_{bj} \quad 1 \le j \le k_{bj} \qquad (6)$$

Where:

$$v_{ai} = value\ of\ the\ i^{th}\ state\ of\ v_a \qquad (7)$$

$v_{bj} = value\ of\ the\ j^{th}\ state\ of\ v_b$ (8)
$p_{ai} = probability\ of\ v_a = v_{ai}$ (9)
$p_{bj} = probability\ of\ v_b = v_{bj}$ (10)

$k_{ai} = state\ number\ of\ v_a$ (11)
$k_{bj} = state\ number\ of\ v_b$ (12)

And the two random variables expressed in the UGF representing the probability mass function *(pmf)* of a set of two discrete random variables, are defined as polynomials as:

$$u_a(z) = \sum_{i=1}^{k_a} p_{ai} z^{vbj} \quad (13)$$

$$u_b(z) = \sum_{j=1}^{k_b} p_{bj} z^{vbj} \quad (14)$$

Where:

$u_1 = UGF\ of\ v_1$ (15)
$u_2 = UGF\ of\ v_2$ (16)

To analyze a system in terms of its components, the u functions of each of these components are combined using a composition operator $\underset{\varphi}{\otimes}$, where φ denotes the composition function to be applied to the exponents in the UGFs for each component (Taboada, et al, 2007). Below, a representation of the u-function, U(z), with the composition operator is shown:

$$U(z) = u_a(z) \underset{\varphi}{\otimes} u_b(z) = \sum_{i=1}^{K_{ai}} p_{ai} z^{v_{ai}} \underset{\varphi}{\otimes} \sum_{j=1}^{K_{bj}} p_{bj}\, z^{v_{bj}} = \sum_{i=1}^{K_{ai}} \sum_{j=1}^{K_{bj}} p_{ai} p_{bj}\, z^{\varphi(v_{ai}, v_{bj})} \quad (17)$$

When a system has multiple elements connected in parallel, its u-function is obtained by the sum of the elements. The u-function takes the form the summation operator ($\underset{+}{\otimes}$) shown below:

$$u_a(z) \underset{+}{\otimes} u_b(z) = \sum_{i=1}^{K_{ai}} \sum_{j=1}^{K_{bj}} p_{ai} p_{bj}\, z^{(v_{ai} + v_{bj})} = u_a(z) u_b(z) \quad (18)$$

And when the system is connected in series, the u-function is modified to take the form of the minimization operator ($\underset{min}{\otimes}$):

$$u_a(z)\underset{min}{\otimes}u_b(z) = \sum_{i=1}^{K_{ai}}\sum_{j=1}^{K_{bj}} p_{ai}p_{bj}\, z^{min(v_{ai}+v_{bj})} \quad (19)$$

In the next chapter is found some of the work previously done utilizing the UGF. This powerful tool has been used in a wide variety of fields, such as analyzing the reliability of a manufacturing plant, to testing the reliability of a power plant as well as the network reliability among others.

6. LITERATURE REVIEW

There are multiple authors that have performed research with the Universal Generating Function. In this paper (Huang *et al* 2007), points out the limitation of application in the continuous stress-strength interference (SSI). In their research paper, stress and strength are evaluated as discrete random variables and the universal generating function (UFG) method is introduced by suggesting discrete SSI model. They validated the effectiveness of their proposed model in different case studies, in which stress and strength are represented by continuous random variables, discrete random variables, or in two groups of experimental data.

In the research paper presented by (Li & Zio 2012), propose an analytical multi-state modeling approach for the reliability assessment of distributed generation systems. In their proposed approach, *so and so*, utilize variety number of renewable energy generation methods along their proposed system. Their application is considered a multi-state system because more than one state is being treated, for instance, the weather, such as sunlight or wind speeds are stochastic in nature as well as the mechanical degradation of the generation systems. Their method of application the UGF is by introducing a multiplication-type composition operator to combine the mechanical degradation and the renewable energy generation source states into the UGF of the renewable generator power unit. Loss of load expectation (LOLE) and expected energy not supplied (EENS) are gauged from the distributed system generation and load UGF's.

In his work, (Yeh, 2009), presented a straightforward algorithm for determining all the minimal paths (MP) prior to calculating the binary-state network reliability between the source node and the sink node. In planning and designing the control of the systems and

the MP set is an elemental means for appraising the network reliability. Their algorithm is based in the universal generating function method while a generalized composition operator is added. In their paper, some case studies are presented to determine the complexity of their proposed algorithm and to depict how the minimal paths are generated. Similarly, (Levitin, 2003) extends the universal generating function technique used for the analysis of multi-state systems to the case when the performance distributions of some elements depend on states of another element or group of elements.

The work from (Jafary & Fiondella, 2016) is represented in this paper, where, to be able to grant correlation between the factors compromising a multi-state component they propose an extension to the discrete universal generating function approach for multi-state systems. The method generalizes to the continuous case and obliges failures to follow ay life distribution. The approach permits the use of sensitivity analysis on the impact of correlation as well as the implementation of efficient performance and reliability assessment; this can be rooted back to the analytical form the approach possesses. In addition, the sensitivity analysis can be practiced to a variety of measures, including performance, reliability, the density function, hazard rate, mean time to failure, availability and mean residual life. Their paper includes some examples where they demonstrate the approach's efficiency to assess performance and reliability along with the operation of the sensitivity analysis.

In this paper, (Levitin *et al)*, concentrate in using the genetic algorithm approach and the universal generating function technique to solve problems of power system reliability optimization. In their work they describe a redundancy optimization problem as the problem of total investment cost minimization, subject to reliability constraints. Since

this approach is being tested in a power system, in this case, reliability refers to the system's ability to supply the required or asked demand of electrical energy. They are also considering the outage effect for units with different nominal generating capacity, therefore, capacities of power system components are considered along with the consumer load curve. To solve the redundancy optimization problem, they used the genetic algorithm, a technique inspired by the principle of evolution, and the universal generating function to determine fast reliability estimation of a multi-state power system. Using these techniques, a set of solutions are found.

Levitin & Lisnianski, (1999) worked with a method that evaluates the importance and the sensitivity analysis of a multi-state system using the universal generating function. Their method presented, is intended for complex series-parallel multi-state systems with a different physical nature of performance and considers a required performance since it furnishes an effective importance analysis tool. In addition, the method examines the sensitivity analysis of the system's output performance measures, such as the mean system performance and the mean unsupplied demand during operating period. To conclude, the added numerical examples to test their proposed method.

Ding et al, (2011) focused in the long-term reserve expansion of power systems with high wind power penetration using the universal generating function methods, they have realized that due to the stochastic of wind speeds, the reliability-based reserve expansion is a major problem of system panning and operation. What *so and so*, present in their paper is a study of the impact of high wind power penetration on the system reserve with the universal generating function determine the reliability from long term planning point of view. The universal generating functions represent models of wind farms

and generators, while the special operators for these UGF's are interpreted to evaluate the customer and the system reliability.

Delgado & Dominguez-Navarro (2014), proposed a method on which they determine the optimal design of a hybrid renewable energy system. It is considered a multi-objective optimization of a generating system, because it considers the objectives of cost of energy, different reliability indexes and the percentage of renewable energy used. The power generation system is made up from solar and wind energies, diesel as conventional energy source and from the grid, too. The universal generating function was used to model the power generating systems and loads with multi-states (two or more performing states). The proposed system enables the estimation of the reliability indexes of the system, with the minimization of computational time while maintaining satisfactory results.

The study of determining the reliability of a system is benign used in multiple areas, for instance, Youssef & ElMaraghy (2008), presented a paper on which they study the performance analysis of manufacturing systems composed of modular machines using the universal generating function. In their paper, they propose a model to evaluate system availability and production rates for manufacturing systems with multiple functionally parallel production units. The units are multi-state manufacturing units, meaning they can work with multiple parts simultaneously in the production stage. Using the universal generating function allows great performance with a positive efficiency when dealing with complex multi-state manufacturing systems. In their paper they also include a number of case studies where their proposed model demonstrates its capacity and performance.

Li, et al (2014) worked on the random fuzzy extension of the universal generating function approach for the reliability assessment of multi-state systems under aleatory and epistemic uncertainties. They took the inevitable factor of uncertainty in any multi-state system modeling and attempt to handle it effectively. To introduce the random fuzzy variables into the approach, a theoretical extension called Hybrid UGF, in addition, its composition operator is defined. Finally, an algorithm is composed to select probability boxes from the HUGF. Their method is presented with numerical case studies with a comparison with Monte Carlo simulation approach.

The research paper written by Lisnianski & Ding (2009), examines the redundancy analysis for repairable multi-state systems by using a combined stochastic processes methods and universal generating function. They consider two multi-state systems. One can satisfy its random demand and provide resources to the other system to improve the reliability. The method exposed by Lisnianski and Ding is based in the combination of stochastic methods and the universal generating function, for reliability evaluation for the repairable multi-state system with redundancy. In their paper, there are numerical examples that illustrate their proposed method.

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7. CASE STUDY #1

With the idea that day by day people across the country are learning more about the needs and benefits of having sustainable practices, there has been an increase in the number of people leaning more towards using renewable sources for their electricity consumption than the conventional fossil fuel-based sources. With this increase, new technologies are being developed in order the suffice and potentially expand the demand. The following is a proposed algorithm that is used to analyze the reliability of a multi-state, multi-objective renewable energy system, where the goal is to maximize the system's probability of meeting a certain electricity production demand and minimizing the cost it takes to achieve the goal demanded and are presented in the following:

$$\textit{Maximize } R_E\ (x, D_E)$$

$$\textit{Minimize } c(x) = \Sigma_{i=1}^{E} c_{s_i} + c_{t_j}$$

Where R_E is the reliability of the system, D_E the electric demand, c is the cost of renewable energy system, accounting for the s_i solar panels and t_j wind turbines and its different brands i and j.

For this problem, a renewable energy generation system is considered. The system is made up of solar panels and wind turbines. The system is modeled to have the environmental characteristics of the region of El Paso, TX. In comparison to the rest of the country, the region of the city of El Paso is rich in receiving the Sun's energy throughout the year. This city was chosen to develop this test because, using the ATaL orientation, it has a monthly average of 6.51 kWh/m^2/day direct normal irradiation (DNI), which is part of the highest points of radiation in the country. When comparing the data of the annual wind speed in the area and the annual wind speed in the country, it shows

that is right in the national average, meaning the region lacks the richness of the wind as compared with other regions. Since the problem is tested a low electricity demand, it was determined to use the area of El Paso County. Moreover, no other renewable energy source is considered, since in the region selected, these two can provide the necessary demand asked for.

7.1 Solar Panels

The sun is a fundamental factor for the generation of electricity through solar panels, that is why solar panels are not profitable everywhere. It is important to have a region where has a constant solar radiation throughout a year. As mentioned before, the region selected for the testing of the model is the region of El Paso. ***Table 10*** shows the total radiation received during a year, and it is broken down by day of the month for a year. The total radiation received per day is measured by W/m^2/day. To test the algorithm, it was determined that eight different brands of solar panels would be used. Each brand differs in the capacity of the amount of energy generated (W) as well as in the efficiency each panel has, and additionally as the area and price. A full list of the specifications on each of the brands is listed below in ***Table 1***. The list includes a variation of prices and capacity, this in order to have a more varied list of solutions.

To calculate the total solar energy output from a solar panel, the following equation is used:

$$E = A * r * H * PR \qquad (20)$$

Where the A is the surface area of the panel, r stands for the solar panel yield, or the solar panel efficiency, H is the value of the solar radiation, while PR is considered the performance ratio, or the coefficient of losses. Such losses may include:

- Losses due to dust
- Weak radiation
- Inverter losses
- Temperature losses
- Among others

Table 1: **Solar Panel Specifications**

Solar Panels Specifications									
Brand	Min Efficiency (%)	Max Efficiency (%)	Avg. Efficiency (%)	Capacity (W)	Price ($)	Area (m^2)	Length (mm)	Width (mm)	Depth (mm)
Panasonic	19	21.6	20.3	320	360	1.73	1618	1071	140
SunPower	19.1	22.2	20.58	360	500	1.63	1558	1046	46
Solaria	18.7	19.3	19	350	394	1.81	1621	1116	40
LG	16.8	20.3	18.28	350	430	1.73	1700	1016	40
Hyundai	14.2	16.5	15.37	270	210	1.64	1640	998	35
Kyocera	14.75	16.11	15.42	265	200	1.65	1662	990	46
ET Solar	15.37	17.52	16.51	340	240	1.94	1956	992	40
Itek Energy	16.49	18.94	17.71	310	340	1.64	1648	993	51

Having the solar panel specifications, knowing the equations needed to determine the energy yielded, and connecting it with our knowledge of the Universal Generating Function, from Chapter 5, the next step is to obtain the U-functions for each of the solar panel brands. For this, it is important to understand the solar radiation the region of El Paso has received. For that, I took the solar radiation (W/m^2/day) for the past two years, 2016, 2017, and came up with ***Table 10***. The table shows the average solar radiation for each day for the two years this data represents (NREL). This exercise was done using four states, meaning that the solar panels are working in only four different scenarios, when the Solar Radiation reaches 6,500, 7,500, 8,500 or 10,000 (W/m2/day). This numbers were obtained by clustering all of the data to only four numbers, this allows simplicity in the calculations and faster data results.

***Table 2:* Panasonic Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
Panasonic	0.216	1.73	320
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.95
2	7,500	0.333	2.25
3	8,500	0.25	2.55
4	10,000	0.167	2.99

***Table 3:* SunPower Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
SunPower	0.222	1.63	360
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.88
2	7,500	0.333	2.17
3	8,500	0.25	2.46
4	10,000	0.167	2.89

***Table 4:* Solaria Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
Solaria	0.193	1.81	350
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.82
2	7,500	0.333	2.09
3	8,500	0.25	2.37
4	10,000	0.167	2.79

***Table 5:* LG Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
LG	0.203	1.73	350
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.82
2	7,500	0.333	2.10
3	8,500	0.25	2.38
4	10,000	0.167	2.80

Table 6: **Hyundai Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
Hyundai	0.165	1.64	270
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.40
2	7,500	0.333	1.62
3	8,500	0.25	1.84
4	10,000	0.167	2.16

Table 7: **Kyocera Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
Kyocera	0.1611	1.65	265
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.38
2	7,500	0.333	1.59
3	8,500	0.25	1.80
4	10,000	0.167	2.12

Table 8: **ET Solar Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
ET Solar	0.1752	1.94	340
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.77
2	7,500	0.333	2.04
3	8,500	0.25	2.31
4	10,000	0.167	2.72

Table 9: **Itek Energy Solar Panel**

Brand	Max Efficiency (%)	Area (m2)	Capacity (W)
Itek Energy	0.1894	1.64	310
State	Solar Radiation (W/m2/day)	Probability	Energy Output (kWh/day)
1	6,500	0.25	1.61
2	7,500	0.333	1.86
3	8,500	0.25	2.11
4	10,000	0.167	2.48

Table 10: **El Paso Solar Radiation**

DNI (W/m²/day)												
Day	January	February	March	April	May	June	July	August	September	October	November	December
1	8,525	4,623	5,531	7,629	5,472	11,364	7,759	1,010	10,089	10,086	4,575	7,797
2	8,593	3,836	6,742	7,260	11,131	11,533	8,649	1,590	10,056	10,258	7,231	4,845
3	8,580	8,489	4,642	10,784	11,153	10,511	9,850	2,400	9,226	10,270	1,462	6,986
4	3,777	8,889	3,098	7,119	11,345	11,432	8,967	3,708	8,997	10,122	6,546	942
5	5,623	3,560	10,086	7,377	11,046	11,515	8,495	4,789	3,300	10,108	1,815	7,517
6	9,019	4,147	7,093	7,563	10,692	11,433	6,005	10,161	5,066	8,403	1,774	4,380
7	8,805	6,985	9,554	10,656	8,723	11,692	10,055	6,665	709	8,492	8,719	8,208
8	8,657	8,564	5,184	10,615	11,354	11,409	9,377	2,498	5,718	9,326	8,767	6,772
9	4,580	9,344	7,527	10,566	11,326	11,494	9,840	3,239	9,502	9,025	9,004	3,301
10	8,714	6,983	10,149	8,528	11,274	11,146	8,771	5,188	9,665	9,558	8,763	8,061
11	8,674	9,569	10,311	5,429	11,153	11,124	9,324	4,796	879	8,723	8,661	8,134
12	7,503	9,772	10,168	3,549	11,299	8,788	5,968	3,909	1,625	9,508	6,483	6,797
13	9,014	9,595	10,160	10,835	11,247	7,466	5,366	7,729	5,578	9,732	8,651	7,240
14	8,989	7,939	8,307	10,595	11,449	11,099	4,545	3,109	2,942	9,731	8,540	8,609
15	8,907	9,823	5,530	9,927	11,477	11,397	9,064	7,794	2,377	9,690	8,232	6,746
16	8,868	7,954	10,541	10,823	11,032	11,133	5,292	7,212	1,178	9,381	3,158	5,381
17	8,898	4,134	10,700	10,596	10,939	9,006	8,472	8,450	5,425	9,341	8,451	3,545
18	8,975	9,202	9,808	4,617	9,774	7,841	9,880	9,260	366	6,745	9,111	3,466
19	7,312	3,974	9,330	4,171	9,161	8,546	9,018	7,241	8,478	2,777	8,049	8,468
20	8,964	10,152	9,098	10,347	9,730	7,009	7,418	9,070	8,372	6,700	8,862	8,482
21	9,015	6,652	6,482	10,505	9,452	9,485	7,322	8,128	6,535	6,921	6,343	8,309
22	4,004	9,228	7,452	6,604	4,116	11,034	7,184	2,308	582	6,853	8,066	8,238
23	5,648	7,894	8,948	10,372	9,058	7,924	9,265	10,082	7,987	9,153	8,672	7,736
24	8,743	4,523	10,271	11,061	9,615	10,390	10,152	7,167	7,579	9,206	9,077	8,721
25	6,893	2,746	5,734	8,911	9,244	9,342	10,165	3,054	9,541	9,332	8,879	3,103
26	8,748	7,402	10,177	6,408	9,239	11,276	10,178	4,435	9,531	8,998	8,648	100
27	5,722	9,800	10,306	9,897	11,257	11,240	7,221	4,344	9,676	3,981	8,593	2,787
28	8,636	9,777	10,474	10,828	10,498	11,124	5,054	9,952	8,703	9,294	8,775	8,589
29	9,059	-	9,782	11,216	6,434	11,159	6,387	9,746	8,627	9,150	8,687	8,886
30	7,602	-	6,564	11,021	7,715	11,000	8,053	9,967	9,931	9,345	6,885	7,450
31	5,394	-	10,673	-	10,104	-	4,486	9,970	-	7,248	-	951

7.2 Wind Turbines

For a wind turbine be able to work, the primary factor needed is wind. As it has already been stated in previous chapters, the wind speed varies by location. And as it is shown in ***Figure 13***, when the El Paso region's average annual wind speed is compared to the rest of the country, it falls under the average or right below the average.

The value calculated of the wind speed will vary depending on the altitude the wind is being measured on. The higher the altitude, potentially the higher wind speed. Additionally, the air density varies accordingly to the temperature of the environment. To determine the total amount of energy generated from a wind turbine, it is necessary to have several sets of data that include the wind speed of a selected location as well as the air density. The air density depends on the temperature of the environment, using the weather data previously obtained from the National Renewable Energy Laboratory, and from the Thermodynamics: An Engineering Approach (Cengel, Boles & Kanoglu, 2015), it can be determined what air density to use for any scenario. For this model, there are five different wind turbines taken into consideration. All the turbines have a generating capacity of 1 kW, but their Cut-In speed, their rated Speed, and the price varies in all of them.

Table 11: **Wind Turbines Specifications**

Wind Turbines Specifications						
Brand	Cut-In Speed (m/s)	Rated Speed (m/s)	Cut-Out Speed (m/s)	Capacity kW	Price (US Dollars)	Rotor Diameter (m)
Excel	2.5	11	-	1	1,470.00	2.50
Aeolos	1.5	10	-	1	2,100.00	2.00
A & C Green Energy	2	9.4	-	1	1,128.93	3.00
Atlantis	3	9	-	1	1,500.00	3.10
Bergey	2.5	11	-	1	4,595.00	2.50

The equation used to determine the total amount of power generated by a wind turbine is the following:

$$Power = \frac{1}{2} * \varepsilon * \rho * \pi * d^2 * v^3 \qquad (21)$$

Where:

$$\varepsilon = efficiency\ of\ the\ wind\ turbine\ \ (\%) \qquad (22)$$

$$\rho = air\ density\ \ \left(\frac{kg}{m^3}\right) \qquad (23)$$

$$d = diameter\ of\ the\ turbine's\ rotor\ \ (m) \qquad (24)$$

$$v = wind\ velocity\ \ \left(\frac{m}{s}\right) \qquad (25)$$

Table 12: **Excel Wind Turbine**

Brand	EFFICIENCY	Rotor Diameter (m)	Capacity (Kw)
Excel	0.4	2.5	1
State	Probability	Wind Speed	Energy Output / Day (kWh/day)
1	0.26	2.55	3.54
2	0.333	3.1	3.88
3	0.25	3.65	4.21
4	0.167	4.28	4.59

***Table 13:* Aeolos Wind Turbine**

Brand	EFFICIENCY	Rotor Diameter (m)	Capacity (Kw)
Aeolos	0.4	2	1
State	Probability	Wind Speed	Energy Output / Day (kWh/day)
1	0.26	2.55	3.23
2	0.333	3.1	3.50
3	0.25	3.65	3.77
4	0.167	4.28	4.07

***Table 14:* A&C Green Energy Wind Turbine**

Brand	EFFICIENCY	Rotor Diameter (m)	Capacity (Kw)
A & C Green Energy	0.4	3	1
State	Probability	Wind Speed	Energy Output / Day (kWh/day)
1	0.26	2.55	3.91
2	0.333	3.1	4.33
3	0.25	3.65	4.74
4	0.167	4.28	5.21

***Table 15:* Atlantis Wind Turbine**

Brand	EFFICIENCY	Rotor Diameter (m)	Capacity (Kw)
Atlantis	0.4	3.1	1
State	Probability	Wind Speed	Energy Output / Day (kWh/day)
1	0.26	2.55	3.85
2	0.333	3.1	4.25
3	0.25	3.65	4.65
4	0.167	4.28	5.11

***Table 16:* Bergey Wind Turbine**

Brand	EFFICIENCY	Rotor Diameter (m)	Capacity (Kw)
Bergey	0.4	3.5	1
State	Probability	Wind Speed	Energy Output / Day (kWh/day)
1	0.26	2.55	4.16
2	0.333	3.1	4.63
3	0.25	3.65	5.09
4	0.167	4.28	5.63

Table 17: **El Paso Wind Speed**

Wind Speed Avg (m/s)												
Day	January	February	March	April	May	June	July	August	September	October	November	December
1	2.7	4.51	5.34	5.39	3.85	3.59	4.36	2.59	3.07	3.44	4.4	2.71
2	3.31	2.04	3.95	6.7	1.58	2.34	3.57	3.82	2.24	2.92	3.94	1.63
3	2.53	3.98	2.73	4.33	2.22	2.67	2.92	3.03	2.6	1.82	1.8	1.6
4	5.36	5.07	1.62	4.12	3.24	2.44	2.34	2	3.37	2.12	3.43	3.21
5	2.95	3.77	3.44	4.66	4.42	2.59	2.02	1.27	2.02	3.57	2.1	2.21
6	2.67	2.83	2.6	4.02	5.8	3.55	1.44	1.88	3.77	2.77	3.11	4.79
7	1.47	3.18	4.33	4.14	5.6	3.1	1.74	1.7	3.06	2.59	1.79	2.52
8	2.57	3.22	3.62	2.09	3.68	2.9	1.49	0.93	2.43	1.62	3.92	3.24
9	3.17	4.33	2.01	2.48	2.95	3.17	2.33	0.73	3.62	3.63	1.99	3.77
10	4.66	4.31	2.57	3.71	4.22	3.14	2.42	2.63	2.44	2.29	5.62	1.49
11	1.7	2.63	5.07	2.68	6.52	4.64	2.6	4.07	2.19	1.49	3.32	1.18
12	5.18	2.74	4.78	5.85	2.75	3.37	2.99	2.96	4.18	4.81	3.7	1.77
13	3.77	3.47	3.25	5.84	4.46	3.21	1.85	1.58	3.83	1.93	3.05	4.3
14	3.53	2.77	3.7	3.47	3.09	4.78	1.77	1.38	3.55	1.97	1.95	4.47
15	2.05	2.8	5.36	3.22	2.32	4	1.91	1.58	2.59	1.8	4.49	1.81
16	2.88	3.92	3.3	3.73	2.46	3.65	2.61	1.82	2.63	1.85	4.72	3.6
17	1.42	2.97	4.27	3.25	2.62	3.45	2.68	1.54	2.25	2.05	2.31	4.49
18	2.2	3.09	4.81	4.67	4.01	3.78	1.67	1.73	1.76	4.74	1.53	1.83
19	1.8	4.96	2.25	2.09	4.66	1.73	2.52	2.79	1.38	4.09	0.92	1.82
20	3.38	3.88	2.03	2.42	3.32	3.76	2.74	3.03	1.32	2.64	2.42	1.58
21	2.39	2.62	4.62	2.2	3.2	2.96	2.89	2.47	2.65	2.39	1.88	3.91
22	1.4	3.45	3.88	4.94	2.1	3.92	2.66	1.17	2.89	1.33	3.65	4.93
23	4.7	2.58	2.77	5.73	2.03	2.33	3.68	2.07	2.11	0.92	6.32	3.67
24	1.54	1.75	1.7	2.72	3.54	2.55	3.25	2.19	2.23	0.7	3.76	1.21
25	1.57	3.4	4.92	4.11	2.92	3.08	1.88	1.75	2.95	1.15	2.99	5.44
26	4.26	2.51	5.42	7.09	2.86	4.13	2.06	1.24	2.44	2.62	1.79	3.86
27	2.47	4.79	6.36	6.61	2.35	5.4	2.34	1.25	2.56	3.81	2.03	1.08
28	2.78	4.37	3.49	5.77	4.11	3.97	2.13	1.08	2.14	1.7	1.1	2.1
29	2.26	-	2.62	4.19	3.24	3.67	1.81	1.67	2.22	1.98	3.81	3.21
30	5.5	-	4.83	6.08	2.83	4.34	1.61	1.81	3.07	2.41	3.22	4.77
31	6.87	-	4.08	-	3.02	-	2.67	3.02	-	5.51	-	4.21

7.3 Problem Approach

As mentioned in Chapter 5, the use of the Universal Generating function will analyze the reliability of a system. In this case, the system consists of two different kinds of sources, solar and wind, and within those sources, there are multiple sub-sections, brands, that need to be considered. Because of the stochasticity of the environment, the system us modeled as a multi-state system. It is multi-state because the amount of solar radiation and wind, varies dramatically from day to day. It has been decided that the problem will be modeled with four working states, each state represent a probability that the system is working at a certain condition, and if it is working at that condition, then a specific power yielded is obtained.

For the solar panels, ***Tables 2*** through ***Table 9*** indicate the four different states used, its probability and the amount of energy produced based on ***Equation 20***. Similarly, for the wind turbines, ***Table 12*** through ***Table 16*** has the information needed to determine the total energy yielded, from ***Equation 21***. This information will be used to find the u-function of all of the brands, which will take the form of ***Equation 13*** and ***Equation 14***. To have a better understanding, lets take the Panasonic Solar panel (***Table 2***), as an example, where its u-function tales the following form:

$$u_{Panasonic}(z) = 0.25z^{\,1.95} + 0.33z^{2.25} + 0.25z^{2.55} + 0.17z^{2.99}$$

There is a 25 percent chance that the system is working at State #1, and it would generate 1.95 KW. Similarly, a 33 percent opportunity the system works at State #2 with a yield of 2.25 KW, and so on, until State #4. This is the u-function, and the same is performed to the rest of the brands. Since the components are connected in parallel, the

u-functions will be used using the summation operator found in ***Equation 18***. This information will be used the performing while evaluating the fitness of a solution at the Genetic Algorithm.

Referring to ***Section 4.7*** of the Genetic Algorithm, there are three ways to code: in binary, integer, and value encoding. For this study, integer encoding will be used. The following chromosome represents a possible solution from a generation, the first 8 cells or genes represent a solar panel brand and the last five represent a wind turbine brand. Since a constraint exists, which indicates that no more than two products of a brand can be used, then the numbers will vary from 0 to 2.

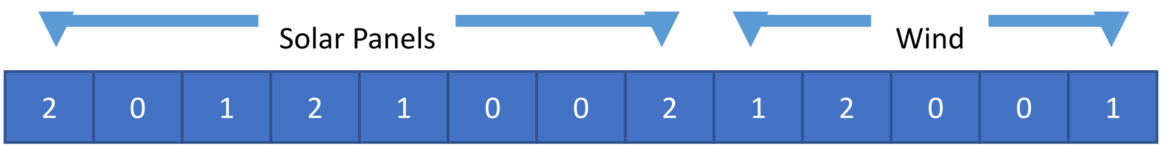

Figure 19: **Possible Solution Representation**

The power yielded by each brand of solar panel and wind turbine while also considering its probability, can be seen from ***Table 2*** through ***Table 9*** and ***Table 12*** through ***Table 16***, respectively. This information is used to obtain the reliability of the system while considering a demand of 50,000 (Wh/day).

7.4 Case Study #1 Results

This problem is treated as a multi-state multi-objective optimization problem, since the purpose of the problem is to obtain a set of solutions, Pareto Solutions, that maximize the total reliability of the system (to achieve a demand of 50Wh/Day) and minimizes the system's total cost. The problem was modeled using a Multi-Objective Evolutionary Algorithm, and the constraints of no more than 2 brands for each system, while using the

Genetic Algorithm parameters of population size of 50, with 20 generations, 30 percent elitism, 10 percent mutation and a single point crossover.

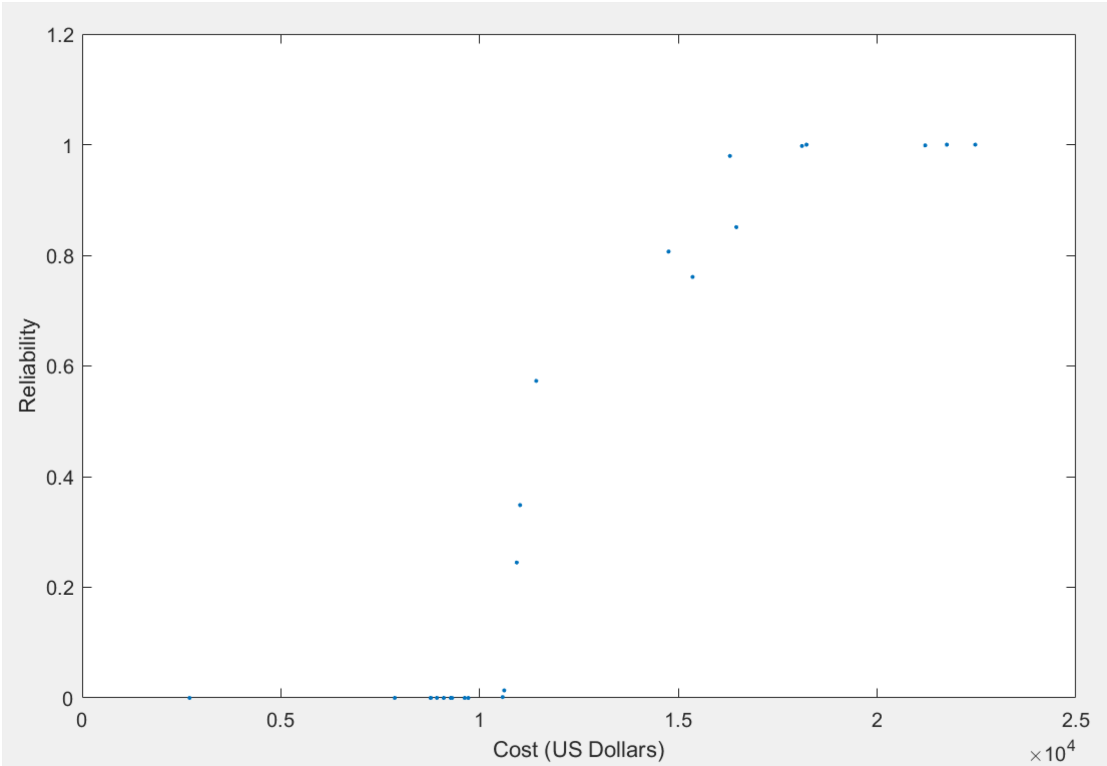

Figure 20: **Case Study #1 Results**

The algorithm was fully coded in MATLAB® 2017 and run on a Lenovo YOGA 910 computer with an Intel CORE i7 processor operating at 2.70 GHz and 8 GB of RAM. The computational time was 653.22 seconds. ***Figure 19*** shows, the 28 nondominated solutions found. The Pareto front is made up of solutions that are distributed at the lower left side of the graph, and through the upper right side. Each of these 28 nondominated solutions are a possible feasible solution to the problem. Nonetheless, since the problem is taken as a multi-objective optimization problem, it is necessary to perform a post-Pareto analysis from the non-dominated solutions found, where the decision maker will determine which objective is more important. Therefore, the objective with the highest

importance will have a bigger *weight* than any other objective in the decision-making phase.

8. CASE STUDY #2

As stated previously, the Universal Generating Function has properties that eases the ability to be used in various applications. In the first case study, the Universal Generating Function is applied in a renewable energy, multi state, multi objective system, where the goal is to minimize the cost spent in photovoltaic panels and in wind turbines, while also maximizing the generation of power, targeting a certain energy demand. Similarly, in the second case study, using the Universal Generating Function, it continues the research of Taboada, et al (2007), in determining the optimal configuration of multi-task production systems. It considers the allocation problem of a multi-state multi-task flexible manufacturing system. Its purpose is to determine an optimal configuration that maximizes the probability of achieving the required demand for a specific objective, or the forecasted productivity for each product, while considering the availability of the machines and the minimization of CO_2 emissions each machine discharges.

For this study, the problem considered uses the flexible shop environment with L stages arranged in series. At each stage, $l(l = 1,\ldots,L)$, machines work in parallel, having the total sum of performances of the available machines be the total performance at each stage. The system also has K different products, where any of the products k $(k = 1,\ldots K)$ can be processed at each stage in any of the machines. Furthermore, for each stage l, there are I_1 types of machines available in the market where each of the machines $i(i=I,\ldots I_l)$, has its CO_2 emissions c_i^l, nominal performance g_{ik}^l (performance rate), and availability p_{ik}^l when performing product k. The concept of the problem is to create a series-parallel system that maximizes the probability A_k of meeting a required system performance level, or demand D_k, and minimizes the total CO_2 emissions of the system.

In the United States, industries are accountable for 15 percent of the CO_2 emitted in the country. The objective functions are represented in the following:

Maximize $A_k\ (h, D_k)$ *for* $k=1,\ldots,K$ (26)

Minimize $C(h) = \Sigma_{l-i}^{L}\Sigma_{i=1}^{I_l} h_{il} c_i^l$ (27)

Since there is not a specific configuration that will maximize the probability of meeting a certain demand for all the individual products, the problem becomes a multi-objective problem with a number of *K* objectives that need to be maximized and the minimization of the system's configuration total CO_2 emissions. The case study considered has a set of optimal solutions represented in a Pareto-front.

When a production system is connected in parallel, its u-function can be calculated using the *summation operator*. The accumulated performance of all the machines while performing product *k,* results in the following u-function, *U(z)*, representing the performance *pmf*:

$$U_k^l(z) = \underset{+}{\otimes}\left(U_{1k}^l(z),\ldots,U_{I_l k}^l(z)\right) = \prod_{i=1}^{I_l} \left(u_{ik}^l(z)\right)^{h_{il}} \quad (28)$$

Furthermore, when the multi-state systems stages are connected in series, the *u*-function representing the *pmf* of the efficiency of the whole system while performing product *k*, is calculated using the *min operator* and it is presented as follows:

$$U_k(z) = \underset{\min}{\otimes}\left(U_k^1(z),\ldots,U_k^m(z)\right) = \underset{\min}{\otimes}\left(\prod_{i=1}^{I_1} \left(u_{ik}^1(z)\right)^{h_{i1}},\ldots,\prod_{i=1}^{I_m} \left(u_{ik}^m(z)\right)^{h_{im}}\right) \quad (29)$$

To calculate the system availability of the u-function that represents the performance *pmf* of the entire system while performing product *k*, the following equation is used:

$A_k=\delta(U_k(z), D_k)$ (30)

8.1. Methodology

8.1.1 Initialization

At the first steps of the algorithm, the initial population is developed, and it is represented in an integer chromosome. Each integer at the gene of a chromosome represents the number of machines of that type present in that solution. ***Figure 20*** represents the mapping of a chromosome (genotype) to its corresponding system configuration (phenotype). Essentially, the shown chromosome or solution, indicates there are one copy of the first machine, two of the second machine and one of the third machine that belong to the first subsystem and they are in parallel. Similarly, for the 2nd subsystem, there are two copies of the first machine and one of the third machine. Finally, subsystem 3, is made up of one of machine type two and another copy of machine type three.

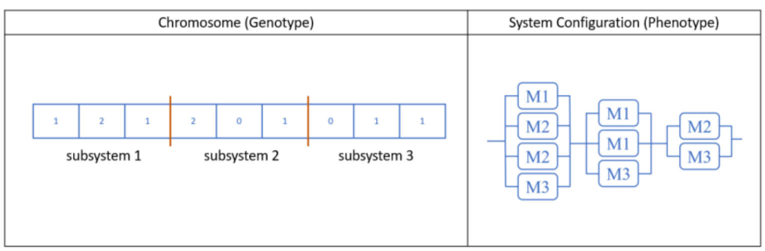

Figure 21: **Representation of System Configuration**

8.1.2 Evaluation of Availability

To determine the availability of a product, an evaluation of each solution is done, with accordance to the objective function. The Universal Generating Function is used to conclude the feasibility of the chromosomes in the population to meet a required demand at each of the individual tasks. The overall CO_2 emissions of the system is determined.

8.1.3 Selection

The moment the solutions have been evaluated, the algorithm analyses the Pareto dominance criterion. The Pareto dominance criterion will indicate which solution, from the

initial population, are dominated and proceed to be eliminated. The dominating solutions will move forward to the next generation.

8.1.4 Evaluation

A distance based, *f*1(*i*) metric is used, which is intended to sustain a population diversity, it gives the highest fitness evaluation to the solutions that are further away from the rest of the solutions in the Pareto front. Also, we implement a dominance count-based, *f*2(*i*) metric, its focus is to select the solutions that are more dominating than others. These solutions are intended to achieve proximity to the true Pareto frontier through an aggregated Fitness Metric, *f*a(*i*), it aims to weight both, Fitness Matric 1 and Fitness Metric 2, equally. Fitness Metric 1 + Fitness Metric 2, *fa*(*i*)= *f*1(*i*) + *f*2(*i*). This aggregated fitness metric is used for the ranking of the solutions (Taboada, et al (2007)).

8.1.5 Crossover and Mutation

New offspring are generated using a problem-specific crossover operation through a predetermined crossover probability. The chance of mutation is implemented through a predetermined probability and it is done using a single point mutation at any random point within the existing chromosome. In this process, elitism is used to prevent the loss of the best solutions found within the generation. A new population is formed with the newly generated offspring and with the elite individuals found during the Ranking process of the previous generation.

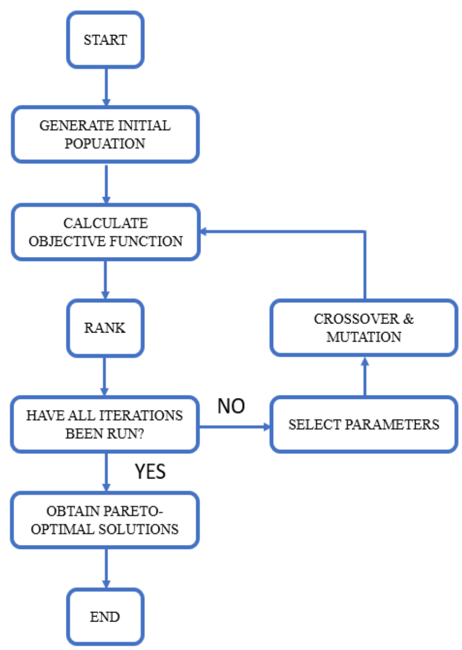

Figure 22: **Algorithm Flowchart**

8.1.6 Stopping Criteria

If the algorithm has reached the predetermined maximum number of iterations, then stop, and return the best solutions in the current population. If the algorithm has not completed the maximum number of iterations, return to Evaluation of Availability and complete the process until termination criteria is met.

8.2 Case Study #2 Results

An example is considered to demonstrate the problem deliberated. In this case, the example has three manufacturing stages connected in series. Each series have subsystems with different machines available in the market. Each machine can perform three different products and for those products, the machine either functions with normal capacity (1) or totally fails (0). In addition, each machine i in the subsystem l has its CO_2 emissions c^l_i, availability p^l_{ik} and nominal performance g^l_{ik} when performing product k. Three objectives were considered: maximization of the availability of producing product 1, maximization of the availability of producing product 2, maximization of the availability of producing product 3, and minimization of the overall CO_2 emissions. The algorithm had a population size of 200 with 20 generations and 5 as the maximum number of machines to be used in each subsystem with the following data:

Table 18: **Case Study #2 Parameters**

Subsystem	l	1									2									3								
Machine	i	1			2			3			1			2			3			1			2			3		
Task	k	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Availability	p^l_{ik}	0.7	0.8	0.9	0.6	0.75	0.8	0.88	0.84	0.65	0.75	0.68	0.82	0.79	0.58	0.76	0.6	0.9	0.57	0.85	0.91	0.85	0.71	0.78	0.6	0.73	0.69	0.8
Production rate	g_{ik}^l	100	200	120	90	160	180	75	180	200	120	160	150	100	178	100	130	150	180	400	200	150	450	220	270	300	280	220
CO2 Emissions	per machine	675			623			519			1246			1558			2077			2077			1973			2492		

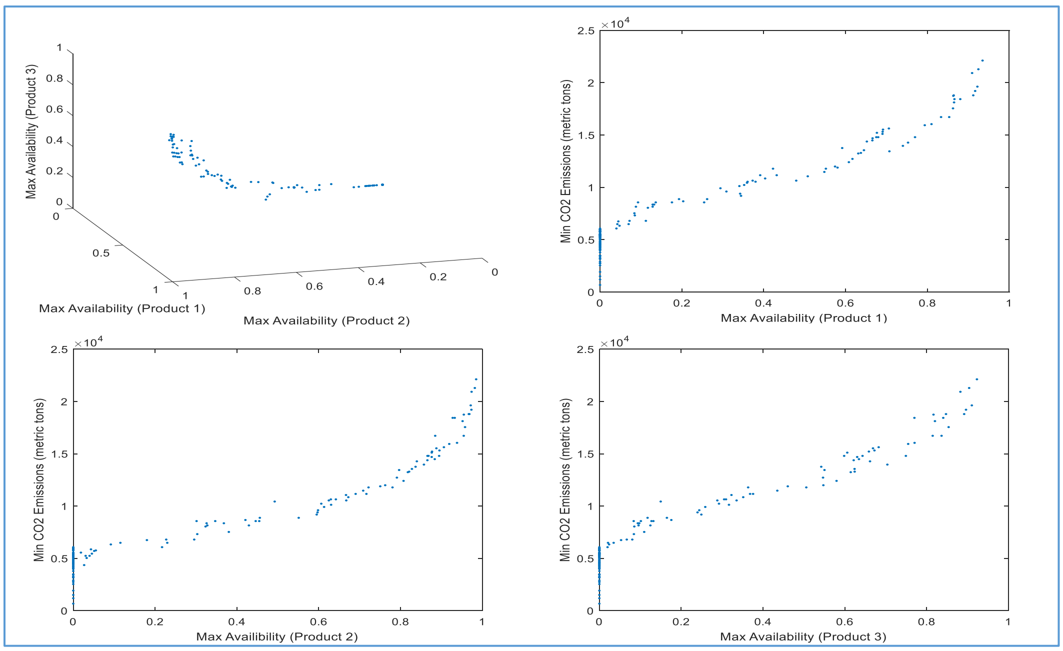

Figure 23: **Case Study #2 Results**

The algorithm was fully coded in MATLAB® 2017 and run on a Lenovo YOGA 910 computer with an Intel CORE i7 processor operating at 2.70 GHz and 8 GB of RAM. The computational time was 10.53 seconds. ***Figure 23*** shows, in three and two-dimensional graphs, the 114 nondominated solutions found. The three-dimensional graph shows how the solutions found are distributed across taken into consideration the three products. The

rest of the graphs compares each product availability to the total CO_2 emissions. Each of these 114 nondominated solutions are a possible feasible solution to the problem. Nonetheless, since the problem is taken as a multi-objective optimization problem, it is necessary to perform a post-Pareto analysis from the non-dominated solutions found, where the decision maker will determine which objective is more important. Therefore, the objective with the highest importance will have a bigger *weight* than any other objective in the decision-making phase.

9. CONCLUSION

The purpose of this paper was to utilize the Universal Generating Function in two different scenarios. Using two types of renewable energy sources, the sun and the wind, the paper demonstrated a new technique to identify the reliability of a renewable energy system. This tool allows the user to identify the areas in which a certain configuration will give a higher percentage of reliability. Using the weather data from the National Renewable Energy Laboratories from the Department of Energy, it was possible to identify the four states in which the problem was tested. The problem was treated as a multi-objective optimization problem, hence the maximization of reliability and minimization of cost. Using a Multi-Objective Evolutionary Algorithm, the problem was solved, finding 28 different nondominated solutions.

In addition, this paper also demonstrated a new multiple objective evolutionary algorithm with the main objective of obtaining the optimal configuration of a multi-state, flexible manufacturing system while trying to maximize the overall system availability and minimize the overall system CO_2 emissions. To be able to obtain a qualified configuration that maximizes the probability of achieving the required demand for a specific objective, or the intended productivity for each product, availability was used in the context of flexible production systems. The problem was treated as a multi-objective optimization problem since a specific configuration may not concurrently maximize the probability of meeting the demand of minimization of CO_2 and all the objectives of the individual tasks. The problem was solved using a Multi-Objective Evolutionary Algorithm, finding 114 different nondominated solutions.

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This thesis was typed by Luis Ernesto Ramirez.