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Multi-Objective System Design Optimization Considering Environmental Emissions

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MULTI-OBJECTIVE SYSTEM DESIGN OPTIMIZATION CONSIDERING

ENVIRONMENTAL EMISSIONS

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Dedication

To my parents, brothers and my sister

For all of their support, sacrifices and unconditional love throughout my life

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by

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THESIS

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It is quite hard to compile the true list of individuals that have helped me in this journey. However, my family, professors and friends are the biggest contributors to my success. I am grateful to my parents, brothers and my sister for their support, encouragement, understanding, patience and unconditional love.

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Abstract

The well-known reliability optimization problem, the redundancy allocation problem (RAP) involves the simultaneous selection of system components and a design level configuration that can meet several design constraints in order to optimize the predefined objective function(s). The RAP has been predominantly solved as a single objective optimization problem with the reliability of the system to be maximized or system design cost to be minimized. When considered as a multiple objective reliability optimization problem, the system reliability is maximized and the cost and weight of the system are minimized. In this work, the RAP was formulated as a multiple objective optimization problem with the system reliability to be maximized and the cost and environmental carbon dioxide emissions to be minimized. A well-known Multi-objective Evolutionary Algorithm (MOEA) named Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used to solve this multiple objective redundancy allocation problem (MORAP).

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Chapter 1: Introduction

The Redundancy Allocation Problem (RAP) is one of the most well-known and complex reliability design problems. It includes the selection of certain components with the applicable levels of redundancy to maximize the reliability of the system under some predefined constraints. The reliability of the RAP can be increased by distributing redundancies throughout its system while meeting constraints such as weight, cost and time. This problem has been solved in the past primarily with numerous meta-heuristic and mathematical optimization approaches.

In this thesis, the RAP is solved as a multiple objective optimization problem with the system reliability to be maximized and the cost and environmental carbon dioxide emissions to be minimized. A well-known Multi-objective Evolutionary Algorithm (MOEA) named Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used to solve this multiple objective redundancy allocation problem (MORAP).

Solving the RAP has been shown by Chern (1992) to be NP-hard. NP stands for non-deterministic polynomial-time hard and usually refers to decision type problems, search problems, and/or optimization problems. Numerous researchers have attempted to resolve this reliability problem as a single objective reliability problem. However, this imposes a limitation on the maximization or minimization of some of the objectives and one cannot be improved without decreasing the potential of the others. Therefore, a tradeoff with the different conflicting objectives is needed to find the best possible combination that simultaneously optimizes all the objectives. The RAP has been solved by Wang et al (2009) as a multiple objective optimization problem using the Non-dominated Sorting Genetic Algorithm (NSGA-II) algorithm with the system reliability to be maximized and the cost to be minimized. In Taboada & Coit (2007) the RAP was formulated to maximize the system reliability and minimize the total cost and weight

of the system using the NSGA-II algorithm. In this research, the RAP was formulated to maximize the system reliability and minimize the cost and equivalent environmental carbon dioxide emissions using the multiple objective redundancy allocation problem data from the above mentioned publication of Taboada & Coit (2007). This was solved utilizing Matlab with the well-known Multiple Objective Evolutionary Algorithm (MOEA) titled (NSGA-II).

The thesis layout is as follows:

Chapter 1 presents an introduction and a description of the motivation for solving the RAP with environmental emissions as one of its objectives along with an analysis of the Life Cycle Assessment methodology. Chapter 2 reviews the multiple objective optimization techniques which include metaheuristics and mathematical approaches to solve the RAP. The most common metaheuristics presented include particle swarm optimization, ant colony optimization and genetic algorithms. Utility theory, goal programming and the weighted sum method are some of the mathematical approaches that are reviewed briefly. In Chapter 3 the Redundancy Allocation problem is discussed both as a single objective and multiple objective problem as well as the methodologies proposed to solve them accordingly. Then in Chapter 4, the multiple objective RAP formulation is presented to allocate the environmental carbon dioxide emissions. It is then followed by a multiple objective optimization example in Chapter 5. To conclude, Chapter 6 presents the concluding statements and future research objectives.

1.1 Global Climate Change

The last few decades have proved the undeniable influence of human activity on the warming and changes of the climate system. Transportation systems and electricity production are among the top contributors to the atmospheric concentrations of the already

existing greenhouse gases in the atmosphere. According to the IPCC report (2007), the accumulation of these greenhouse gases is most likely the source of the observed increasing fluctuation in average global temperatures in the air and ocean, the rise of average sea levels and the extensive melting of snow and glaciers. In the report by the EPA (2010) has published the top most important twenty four indicators that reflect trends caused by climate change over a range of observed time periods.

Climate is defined as the weather conditions including temperature, precipitation, and wind, in a particular region. A misconception about climate change is that it is a year after year variability in weather and storm tracks. However, climate change can be defined as either global cooling or warming (Jacoby et al. 1999). In the following Figure 1 from the Climate Change Indicators in the United States by the EPA report (2010), the global greenhouse effect is shown. As illustrated, the earth's atmosphere is not completely transparent to the infrared radiation (IR) of the sun. The majority of the earth's weather and climate is drawn primarily from the sun's energy. Certain greenhouse gases in the earth's atmosphere absorb the radiated energy from the sun and trap it in this layer that acts as a blanket over the surface and warm it significantly. The greenhouse effect is a naturally occurring cycle that happens naturally to have the cycle of life functioning properly. However, since the mid of the previous century or the industrial revolution era, human activities including burning fossil fuels in power plants and automobiles, waste management practices, and industrial and agricultural processes have increased significantly the presence of these gases.

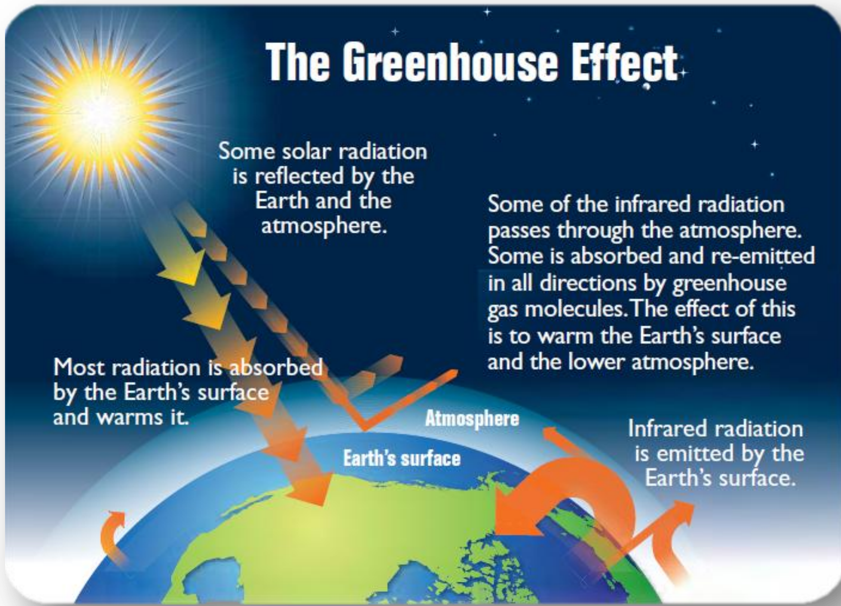

Figure 1: The Greenhouse Effect

According to Tester et al (2005), there exists predominant evidence that points to human influence on global climate change. The report recognizes greenhouse gas emissions, in particular carbon dioxide emissions by human activities as the major factor of increasing global mean temperatures. Figure 2 from NOAA (2010), demonstrates the earth's surface temperatures and the earth troposphere's (earth's lower level of atmosphere) temperatures measured by land-based weather stations and satellite measured data respectively. The UAH and RSS acronyms used below characterize the methods by which the original satellite data was analyzed. According to the report, during this time period analyzed, the average rate of increase in temperatures in the United States is about 0.13° F per decade or 1.3° F per century. However, it can also be observed that since the nineteen seventies, the average

temperatures have quickly escalated from a range of 0.35 to 0.50° F per decade. The graph also illustrates that the consecutive warmest years have occurred since the mid 1990's.

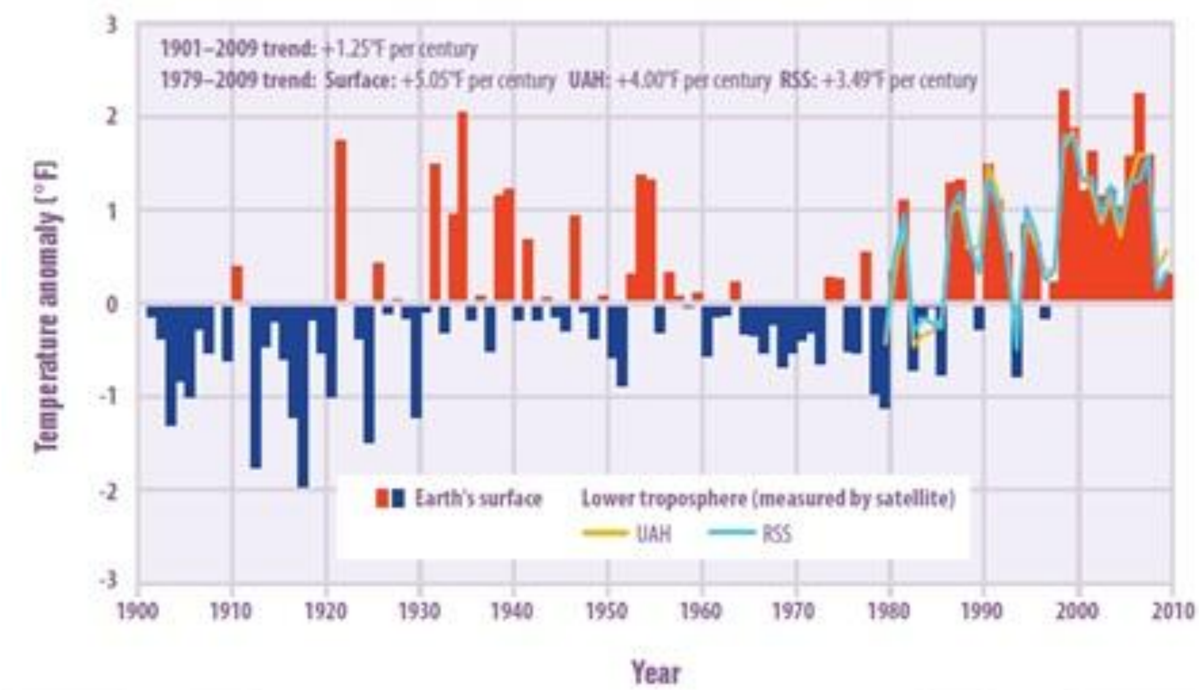

Figure 2: Surface and Troposphere Temperatures in the United States, 1901-2009

The average air temperature registered per state varies and has changed surprisingly in the twentieth century. Figure 3 from NOAA (2009) below illustrates the various rates of temperature change in degrees Fahrenheit per century in the United States from the early 1900's to 2008. As it can be observed, the West, the North, and Alaska have had the highest change in rate of temperature in the country.

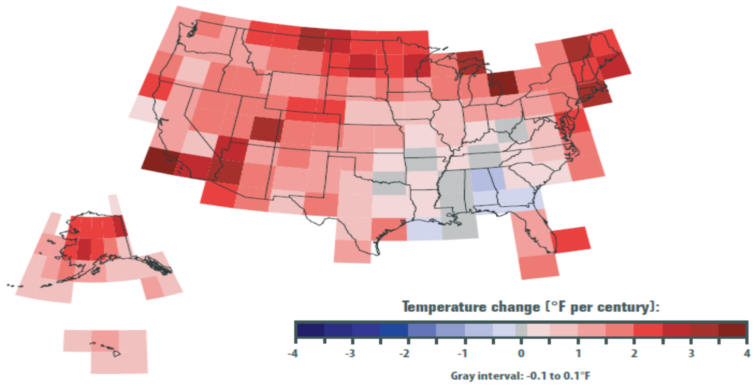

Figure 3: Rate of Temperature Change in the U.S., 1901-2008

The EPA also published in the same report the average air temperatures worldwide from the same time period (1901to 2009). According to Figure 4 (NOAA, 2010) below, the average global surface temperature is quite similar to the average temperature per decade for the United States. However, when comparing the United States to the remaining countries, the report finds that the United States has warmed at almost twice the global rate during the nineteen seventies. In addition, the graph also depicts that the previous most recent decade (2000-2009) has been classified as the warmest worldwide.

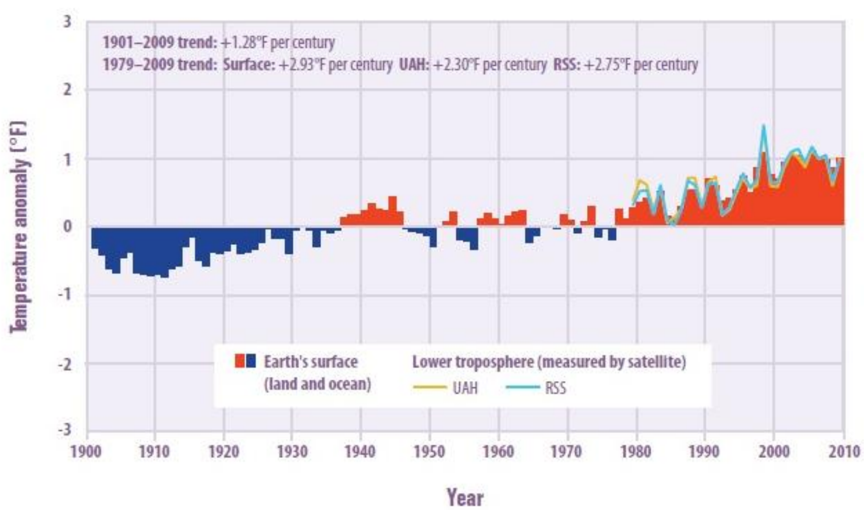

Figure 4: Surface and Troposphere Temperatures Worldwide,
1901-2009

These temperature fluctuations are essential models for climate change analysis, and the effects can range widely on ecosystems and human life. These growths in air temperature may lead to additional and extreme heat waves that can cause illness or even fatalities to the more vulnerable populations. Additionally, temperature patterns control what types of plants and animal species may survive in a specific habitat. If these variations occur abruptly, animal and plant species do not have time to adapt.

As a result of greenhouse gases trapping more energy within the Earth's atmosphere, the average temperature of the Earth's surface is projected to increase more during the upcoming decades and centuries. Some areas around the world might experience more warming or cooling than others because naturally occurring and human driven climate change. Shifts in the currents of the ocean and wind patterns that determine the climate system might occur suddenly. Furthermore, variations in air temperatures may change sea surface temperatures, rainfall patterns, and numerous additional phases of weather and climate.

1.1.1 EPA Environmental Concerns

In Graedel and Allenby (2010), a list has been published of the top seven crucial environmental concerns: Global climate change, loss of biodiversity, stratospheric ozone depletion, human organism damage, water availability and quality, resource depletion: fossil fuels, and land use patterns. Table 1 (Graedel and Allenby 2010) illustrates all of the environmental concerns ranging from crucial to less important.

Table 1: Significant Environmental Concerns

Crucial Environmental Concerns	1. Global Climate Change
	2. Loss of biodiversity
	3. Stratospheric ozone depletion
	4. Human organism damage
	5. Water availability and quality
	6. Resource depletion: fossil fuels
	7. Land use patterns
Highly important environmental concerns	8. Depletion of non-fossil fuel resources
	9. Acid deposition
	10. Smog
	11. Aesthetic degradation
Less important environmental concerns	12. Radionuclides
	13. Landfill exhaustion
	14. Thermal pollution
	15. Oil spills
	16. Odor

These crucial environmental concerns are subject to change in priority as alternative and renewable technologies advance. The first three environmental concerns (global climate change, loss of biodiversity and stratospheric ozone depletion) are related to the global environment effects. Some possible different areas of analysis include any of the life cycle assessment stages that range from some of the most common resource processing phases to analysis of water resource habitats and the rate at which crucial emissions affect the depletion of the ozone. The fourth environmental concern (human organism damage) relates to the adverse effects on the human population by mutagenic, toxic and carcinogenic agents. Lastly, the depletion of fossil fuel resources, the quality and availability of water and the land use patterns pose some possible areas of analysis such as finding alternatives to the discharge of certain water borne toxins, carcinogenic, mutagens, and radioactive material.

1.1.2 Greenhouse Gas Emissions

There exist numerous techniques that might reduce greenhouse gas emissions over time. Some approaches that have been proposed and offer a promising future to minimize greenhouse gas emissions include fuel switching from the conventional existing fossil fuels to hydrogen powered transportation devices, biodiesel utilization as a fuel for a decreased amount of emissions, an efficiency increase for the electric powered vehicles, maximizing the efficiencies of wind power turbines and solar photovoltaic panels, practicing conservation and energy efficiency methods, and recovering methane from emission sources such as landfills.

The primary greenhouse gases in the United States and around the world are carbon dioxide, methane and nitrous oxide. Further in this section, it will be evident from reports of the U.S. EPA that these primary greenhouse gas emissions are quantitatively meaningful. These distinct greenhouse gases are emitted by some of the same human activities. For example, carbon dioxide is produced mainly through the burning of fossil fuels (oil, natural gas, and coal), wood, trees and solid waste. However, changes in land use, such as growing new forests or disturbing soils, may perhaps lead to the accumulation or deduction of carbon dioxide to/from the atmosphere. Methane is very similarly emitted like carbon dioxide. It is primarily emitted during the production and transport of coal, natural gas, and oil. Methane emissions are produced from agricultural practices and the decaying of organic waste in waste landfills. Lastly, nitrous oxide emissions are generated from industrial and agricultural activities and also from the combustion of fossil fuels. Figure 5 (U.S. EPA, 2010) and Figure 6 (World Resources Institute, 2009) below show the top three greenhouse gas emissions both in the United States and worldwide respectively.

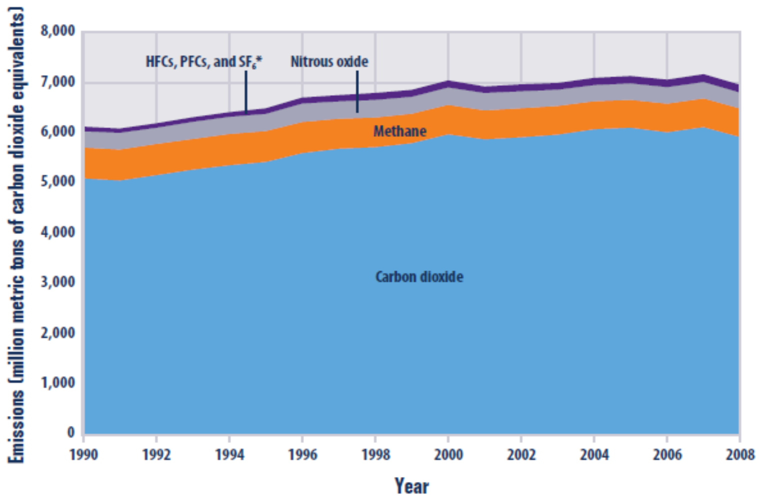

Figure 5: U.S. Greenhouse Gas Emissions by Gas, 1990-2008

At the end of the year 2008, the report indicates that the total U.S. greenhouse gas emissions summed up to around 7,000 million metric tons of carbon dioxide equivalents. This reflected about a fourteen percent increase from the start of the study in 1990. During this time period from 1990 to 2008 of the study, emissions of carbon dioxide increased by 16 percent, methane emissions decreased by 7 percent, and nitrous oxide emissions declined by 1 percent.

The world is estimated to have emitted over 38,000 million metric tons of greenhouse gases, expressed as carbon dioxide equivalents as of the year 2005. In terms of change, this signifies a twenty six percent increase from the year 1990. During this time period of study, the total global emissions of all the primary greenhouse gases have increased. Carbon dioxide emissions have increased by thirty one percent globally and consequently make up about seventy five percent of the world's total global emissions. Methane also increased by about ten percent according to the reported data.

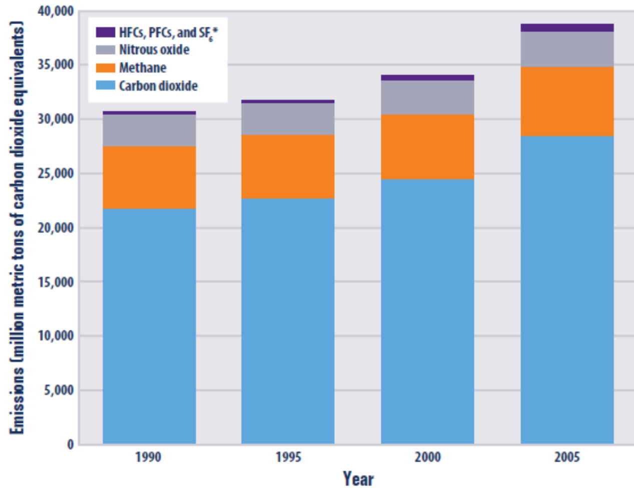

Figure 6: Global Greenhouse Gas Emissions
by Gas, 1990-2005

As it can be observed, in both instances that the top three contributing greenhouse gas emissions in the United States and worldwide are carbon dioxide, methane and nitrous oxide. It is evident that everybody around the world releases greenhouse gases. Therefore, the source of climate change is global. Factors such as economic activity, population, income level, land use, and weather conditions affect the rate at which some countries yield more greenhouse gases than others. Figure 7 (U.S. EPA 2010) shows that thirty two percent of the total greenhouse gas emissions from the United States are primarily derived from electricity generation followed by the transportation sector with twenty seven percent of emissions since the year 1990. The land use, land usage change and forestry sink(s) removed fourteen percent of the total United States greenhouse gas emissions' by the carbon absorption and/or sequestration in agricultural soils, trees, forests and landfilled food and agricultural scraps.

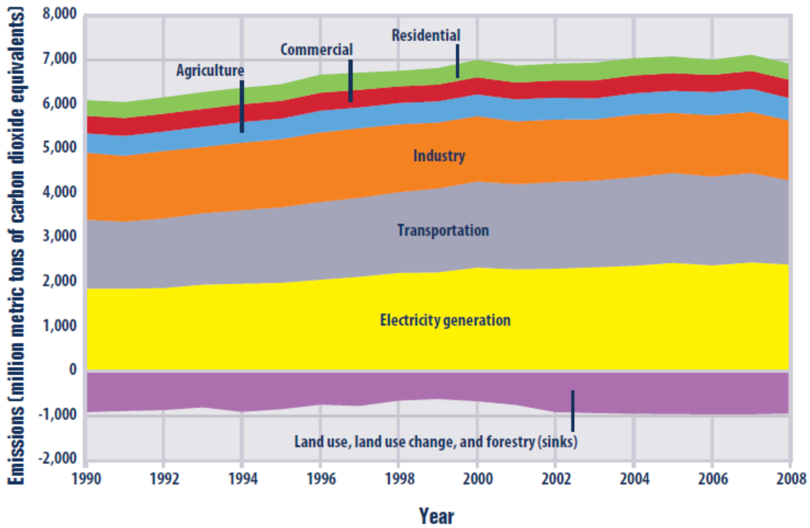

Figure 7: U.S. Greenhouse Gas Emissions
by Economic Sector, 1990-2008

Figure 8 (World Resources Institute, 2009) illustrates the total global greenhouse gas emissions by sector from the time period of 1990 to 2005. Worldwide, energy use is the principal source of greenhouse gas emissions. About seventy percent of the total emissions are generated from the energy generation stage and it is followed by the agricultural sector with about fifteen percent of the total emissions. The previous graph of the United States disclosed land use, land usage changes and forestry as a net sink for greenhouse gases. This meant that they absorb more greenhouse gases than they discharge. However, on the global scale this is not the case. Instead they are considered a supplementary foundation of greenhouse gas emissions.

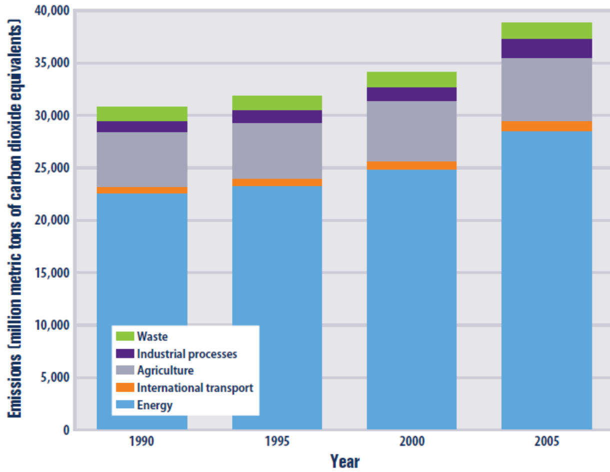

Figure 8: Global Greenhouse Gas Emissions
by Sector, 1990-2005

Global carbon dioxide emissions are increasing at different rates worldwide. As it can be observed from Figure 9 (World Resources Institute, 2009) below, the top three countries include Europe, Asia and the United States. These countries are extremely developed and their competitive technologies should be utilized to minimize their impact on the environment.

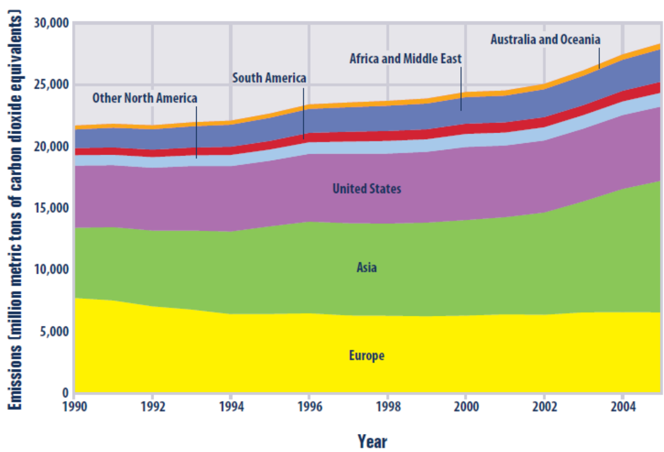

Figure 9: Global Carbon Dioxide Emissions
by Region, 1990-2005

The IPCC report in its' 1995 version published a list of all the possible greenhouse gases and their equivalent global warming potential (GWP). Table 2 (Tester et al. 2010) illustrates the greenhouse gas, the chemical formula, lifetime in years, and the GWP in a time horizon of thirty, one hundred and five hundred.

Table 2: Greenhouse gases and their Global Warming Potential (GWP)

Species[a]	Chemical Formula	Lifetime (years)	Global Warming Potential (Time Horizon)		
			30 years	100 years	500 years
CO_2	CO_2	variable[b]	1	1	1
Methane[c]	CH_4	12±3	56	21	6.5
Nitrous oxide	N_2O	120	280	310	170
HFC-23	CHF_3	264	9,100	11,700	9,800
HFC-32	CH_2F_2	5.6	2,100	650	200
HFC-41	CH_3F	3.7	490	150	45
HFC-43-10mee	$C_5H_2F_{10}$	17.1	3,000	1,300	400
HFC-125	C_2HF_5	32.6	4,600	2,800	920
HFC-134	$C_2H_2F_4$	10.6	2,900	1,000	310
HFC-134a	CH_2FCF_3	14.6	3,400	1,300	420
HFC-152a	$C_2H_4F_2$	1.5	460	140	42
HFC-143	$C_2H_3F_3$	3.8	1,000	300	94
HFC-143a	$C_2H_3F_3$	48.3	5,000	3,800	1,400
HFC-227ea	C_3HF_7	36.5	4,300	2,900	950
HFC-236fa	$C_3H_2F_6$	209	5,100	6,300	4,700
HFC-245ca	$C_3H_3F_5$	6.6	1,800	560	170
Sulphur hexafluoride	SF_6	3,200	16,300	23,900	34,900
Perfluoromethane	CF_4	50,000	4,400	6,500	10,000
Perfluoroethane	C_2F_6	10,000	6,200	9,200	14,000
Perfluoropropane	C_3F_8	2,600	4,800	7,000	10,100
Perfluorobutane	C_4F_{10}	2,600	4,800	7,000	10,100
Perfluorocyclobutane	c-C_4F_8	3,200	6,000	8,700	12,700
Perfluoropentane	C_5F_{12}	4,100	5,100	7,500	11,000
Perfluorohexane	C_6F_{14}	3,200	5,000	7,400	10,700
Ozone-depleting substances[d]	e.g., CFC and HCFCS				

In the study by Stott et al. (2000), it was presented that for the past one hundred years, the complete history of both heating and cooling time frames were not only caused by human factors alone. Instead, it was suggested that also natural occurring forces in the atmosphere combined with the rise in human processes have increased dramatically the greenhouse gases in the underlying layer of the earth; the troposphere. Consequently, a higher amount of energy is reflected back to the earth's surface causing global warming. As stated by Stone (2000), the fundamental question in the science of global warming is: is there a direct relationship between the increases in global average temperatures and atmospheric concentrations of

carbon dioxide? One method that has been attempted to answer this question is through global climate models or general circulation models (GCM). GCM's tend to simulate the three dimensional states of the atmosphere, ocean, biosphere and how they change over time. These models also try to solve the mathematical formulations that express the laws of conservation, material, momentum, and energy of the earth's atmosphere. Tester et al. (2010) mention that at the current state, the most widely acknowledged source of human influence on global climate change is the production of two greenhouse gases during the production and supply of energy from fossil fuels. The generation of carbon dioxide from fossil fuel combustion and leakage of methane from pipelines are some of the most dominant greenhouse gases produced. Figure 10 illustrates the world energy by source and it indicates that currently about 80 percent of the total global energy is supplied by fossil fuels. The emissions of greenhouse gases tend to raise the temperature of the planet. The current temperature increased has been measured to be 0.6 % but it is expected to range between two to four degrees Celsius by the end of this century (Smith & Taylor 2008).

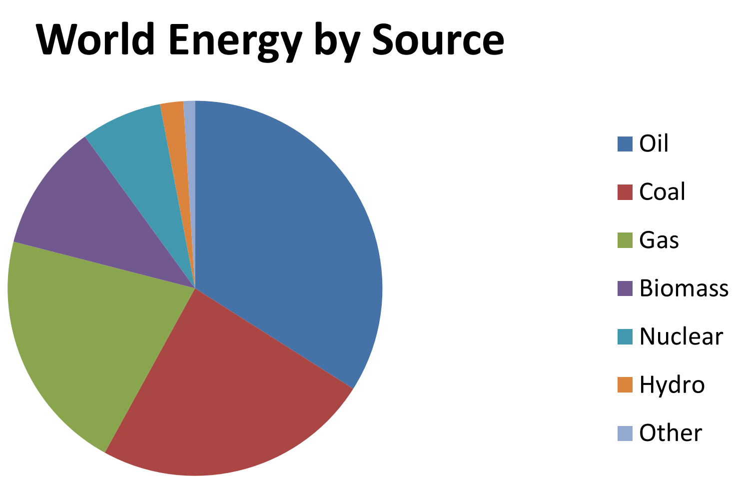

Figure 10: World Energy Outlook by Source

1.1.3 Fossil Fuels

Fossil fuels are hydrocarbon based fuels that were formed from the remains of decayed plants and animals that were captured in geological deposits many centuries ago. Coal, natural gas and oil are the fossil fuels used today for eighty percent of the global energy production (Smith & Taylor 2008). Fossil fuels are considered non-renewable energy source since they take numerous years to replenish after being used and take millions of years to form from plant and animal remains at the bottom of the terrain surface. As countries have developed, fossil fuels are relied on for transportation fuels, electricity production and commercial and industrial processes. Although the wind, water and sun were already being used for energy production, they became less popular as the three primary fossil fuels were used for most of the global energy production. Petroleum is the main fossil fuel used for global energy for transportation, heating, and industrial production. With the increase in automobile utilization, oil usage increased rapidly in the twentieth century. Natural gas is very popular in electricity generation because of its' high yield of energy as compared to coal. In comparison to coal, it generated twice the amount of energy per unit of carbon dioxide (Graedel & Van der Voet 2010). Coal in the early twentieth century dominated the energy markets. It has recognized to be the cheapest fuel for power plants in the majority parts of the world. Fossil fuels are vital for certain industrial processes. Steel production depends on coal and oil production while natural gas is imperative for hydrogen production. Numerous fertilizers, plastics and certain chemicals are also derived from fossil fuels.

1.1.4 Alternative and Renewable Technologies

The difference between an alternative and renewable technology is an imperative distinction that will minimize error in classifying an energy/technology source. Alternative technologies are those that are not derived from fossil fuels but are also considered non-renewable. On the other hand, renewable technologies refer to those that harness energy from an inexhaustible classified source such as the sun, wind, falling water and natural occurring/present direct and indirect forms of energy. Some of those forms of energy might include hydropower, biomass, geothermal, solar, and wind energy.

Hydropower refers to energy that is captured from falling or running water. An exceptional example includes rivers. It can be developed on a small or large scale depending on the required energy output and feasibility to modify the existing terrain surrounding the body of water. The majority of projects are large scale projects where a dam on a river is constructed. The three major types of hydropower plants include an impoundment dam, diversion (run-of-river) and pumped storage. Figure 11 below illustrates a typical hydropower plant.

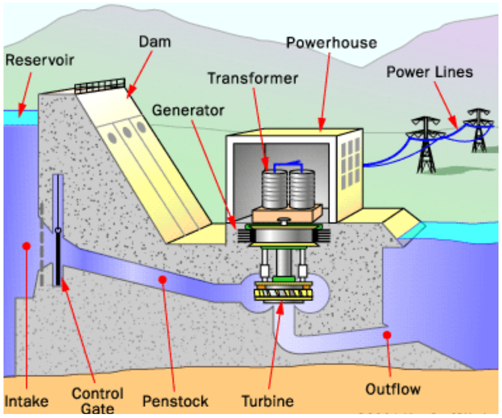

Figure 11: Inside a Hydropower Plant

In the impoundment dam, usually the water is held in a reservoir and the flow of water is directed into a penstock that carries it to the to the turbines that are connected to electric generators. As the water spins through the turbines electricity is generated. The small scale or run of river do not require any damn to be built and hence are more environmental friendly but they also generate less than 50 megawatts of electricity (Pimentel 2004). Some advantages of large scale hydropower sources include low operating costs and longer expected power plant life if compared to any other form of electricity production. They also emit hardly any carbon dioxide and minimal fossil fuel usage is required (Smith and Taylor 2008).

Sources of bioenergy are called biomass and it is a renewable energy technology made from any organic material from plants or animals. Some of these sources include agricultural and forestry residues, municipal solid wastes, industrial wastes, and terrestial or aquatic crops grown for energy purposes. Biomass is considered a renewable resource and an attractive petroleum alternative because it is available globally and can be converted into more environmental friendly liquid transportation fuels (ethanol and biodiesel) and used to generate electricity (Swain et al. 2011). The main types of biomass include virgin wood, energy crops such as corn and sugar cane, agricultural residues, food waste, industrial waste and co-products. Although this type of renewable energy source has gained popularity worldwide, the combustion of biomass gives only about an eighteen to twenty two efficency rate. In Figure 12, (Abbasi & Abbasi 2009) the widely most common biomass to energy conversion processes are shown and their perspective obstacles and advantages are briefly discussed. Many of the challenges exist in increasing the lower efficiency rates of the different processing methods including cofiring, gasification and the pyrolysis. The biodiversity challenges in preserving the land even after being utilized for growing biomass energy crops is another challenge (Fthenakis & Kim 2008).

Biomass-energy option	Problems	Advantages
Food to ethanol (C_2H_5OH)	Very low net energy yield; competition with food crops; air and water pollution; low yield per unit area	Popularly perceived to be a 'green' and 'clean' option, which in reality it isn't
Food crop to butanol (C_4H_9OH)	Net energy yield still quite low even if better than ethanol; competition with food crops; air and water pollution; low yield per unit area	Better net energy yield than ethanol
Lignocellulosic biomass to ethanol or butanol	Unproven at a large scale; low net energy yield; positive attributes may lead to over exploitation and consequent harm to the environment	Higher yield per unit area; cultivable on degraded lands; less severe competition with food crops,; less natural resource degrading then food crops
Zoomass (animal waste) to methane (CH_4)	Conversion efficiency is not yet high enough; presently the unit cost is higher than from natural-gas deposits	Proven technology; can use residues and wastes, turns potential pollutant into an energy resource; CH_4 capture infrastructure is in place
Zoomass to hydrogen (H_2)	Conversion efficiency is very low; far from feasible as of present	Can use residues and wastes; effects pollution control; H_2 can be used in fuel cells
Zoomass to electricity via the microbial fuel cell (MFC)	Technology is nascent; conversion efficiency is not established	Electricity infrastructure is in place; an MFC is a combustionless, pollution free fuel-cell technology that uses renewable organic fuel directly
Hydrocarbon-rich plants to biodiesel	Yield per unit area unproven; competes with food crops; lure of quick benefit may cause diversion of fertile lands to their cultivation	Biodiesel is a high-density fuel that is as efficient as, but less polluting, than petroleum
Phototrophic microorganisms (algae or cyanobacteria) to biodiesel	Technology is at an early stage; may require significant capital investment	Biodiesel is as efficient as but cleaner than petroleum; possible to have very high yield per unit area, does not compete with food crops

Figure 12: Biomass to Energy Conversion Issues

Geothermal technology uses the natural available heat present in the Earth's interior to generate energy. Hot springs, geysers, the earth's core and mantle are composed of very high temperature rock and water. The Earth's internal heat is derived from a combination of residual heat coming from planetary accretion (about twenty percent) and radioactive decay (accounts for up to eighty percent). Temperature within the Earth increases with greater depth. The geothermal gradient is between 25-30° C per kilometer of depth. The Earth's center which is about 6,400 kilometers deep is said to have temperature range between 5,650 ± 600 K (Diesendorf 2007). The most active geothermal resources are usually found along major plate boundaries where earthquakes and volcanoes are concentrated. The Ring of Fire area which encircles the Pacific Ocean (Asia, Australia, North America and South America bounded) is where the majority of geothermal activity in the world occurs (Tester et al. 2005). Table 3 (Earth Policy Institute, 2007) below illustrates the top twenty countries for geothermal capacity and the electricity generation respectively.

Table 3: Worldwide Geothermal Capacity and Electricity Generation

Country	Geothermal Power Capacity	Geothermal Electricity Generation
	Megawatts	Million Kilowatt-hours
United States	2,923.5	15,883
Philippines	1,969.7	12,596
Indonesia	992.0	6,344
Mexico	953.0	6,094
Italy	810.5	5,183
Japan	535.2	3,422
New Zealand	471.6	3,016
Iceland	421.2	2,693
El Salvador	204.2	1,306
Costa Rica	162.5	1,039
Kenya	128.8	824
Nicaragua	87.4	559
Russia	79.0	505
Papua New Guinea	56.0	358
Guatemala	53.0	339
Turkey	38.0	243
China	27.8	178
Portugal	23.0	147
France	14.7	94
Germany	8.4	54

Solar thermal energy systems utilize the sun's rays and convert it into heat. The heat is then used to produce energy. Some of the most popular solar systems range from solar ponds to photovoltaic systems and parabolic troughs. Photovoltaic systems are said to have a large amount of potential to providing the energy needs of the United States and world electrical needs (Tabor and Doran 1990). The photovoltaic cells that are the most favorable in terms of cost, high efficiencies, and massive production capabilities are those made of silicon material. Solar ponds use the sun's radiation to store energy at nearly one hundred degrees Celsius. These ponds have a layered salt concentration gradient that allows convection to occur and hence trap the heat in the bottom area that generates electricity (Pimentel 2004). Parabolic troughs are also utilized for

large-scale energy production. They have the shape of the bottom half of a large drainpipe that reflects sunlight to a central receiving tube that is located above the device. Water and other fluids are typically used to produce steam that initiates generators for electricity production. Figure 13 from the National Renewable Energy Laboratories show the US annual average solar energy received by a latitude tilt photovoltaic cell.

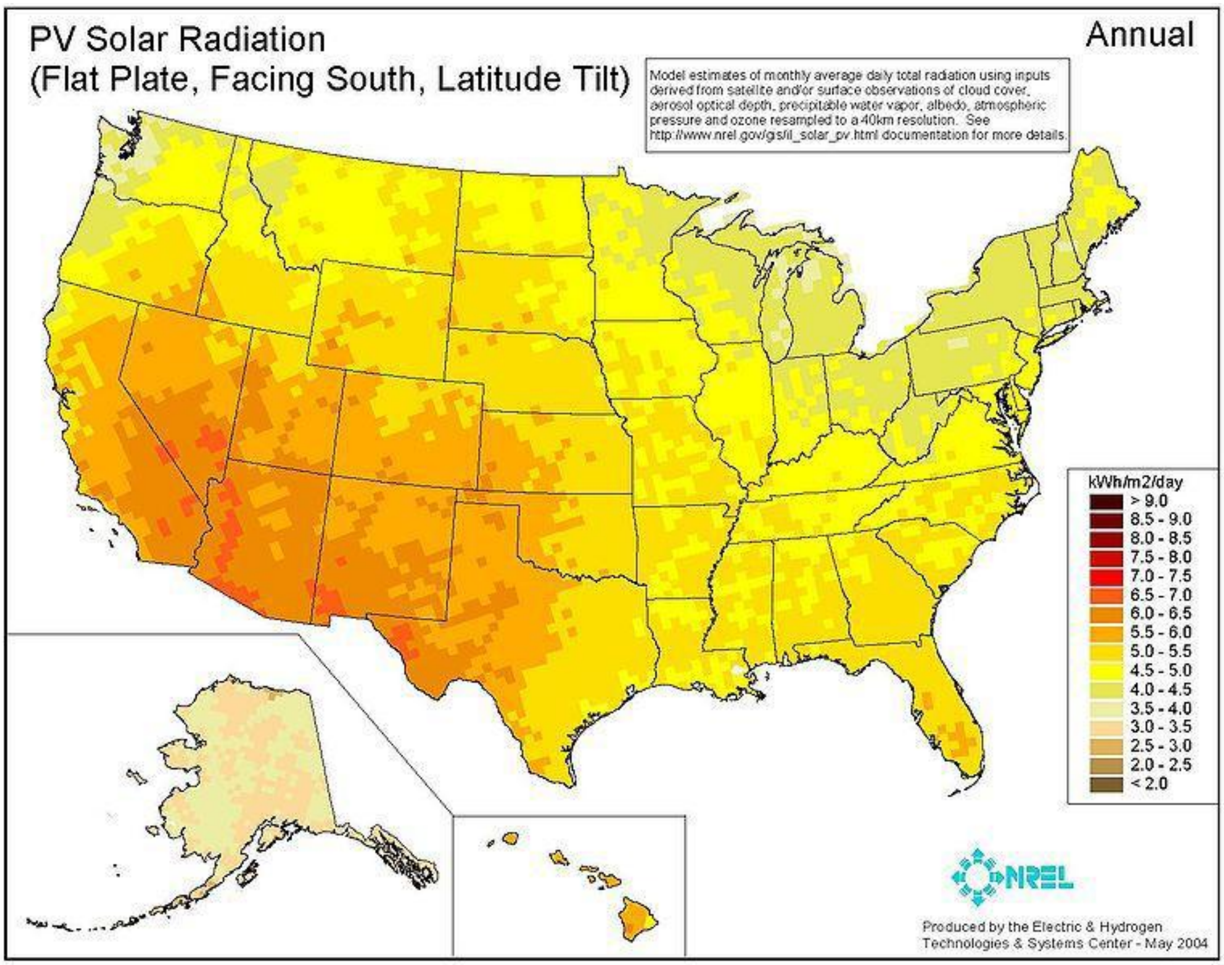

Figure 13: US Annual Average Solar Energy

Wind energy can be dated back to the end of the nineteenth century with the production of the first windmill for electricity production in 1887 by James Blyth in Scotland. However, the modern wind power industry began in 1979 in Denmark. In comparison to the capacities during

the 1980's where the wind turbines only generated between 20-30 kW, nowadays some turbines can deliver up to 7 MW. In 2010, worldwide capacity of wind-powered generators was about 195 GW. In terms of total installed capacity, the top three contributors include China, United States and Germany (Pimentel 2004). Wind energy as a power source is said to be attractive as an alternative to fossil fuels because it is derived from a renewable source, widely distributed and plentiful, and clean in the sense that it produces no greenhouse gas emissions. Figure 14 below from the National Renewable Energy Laboratories indicate that the United States has exceptional wind capacity.

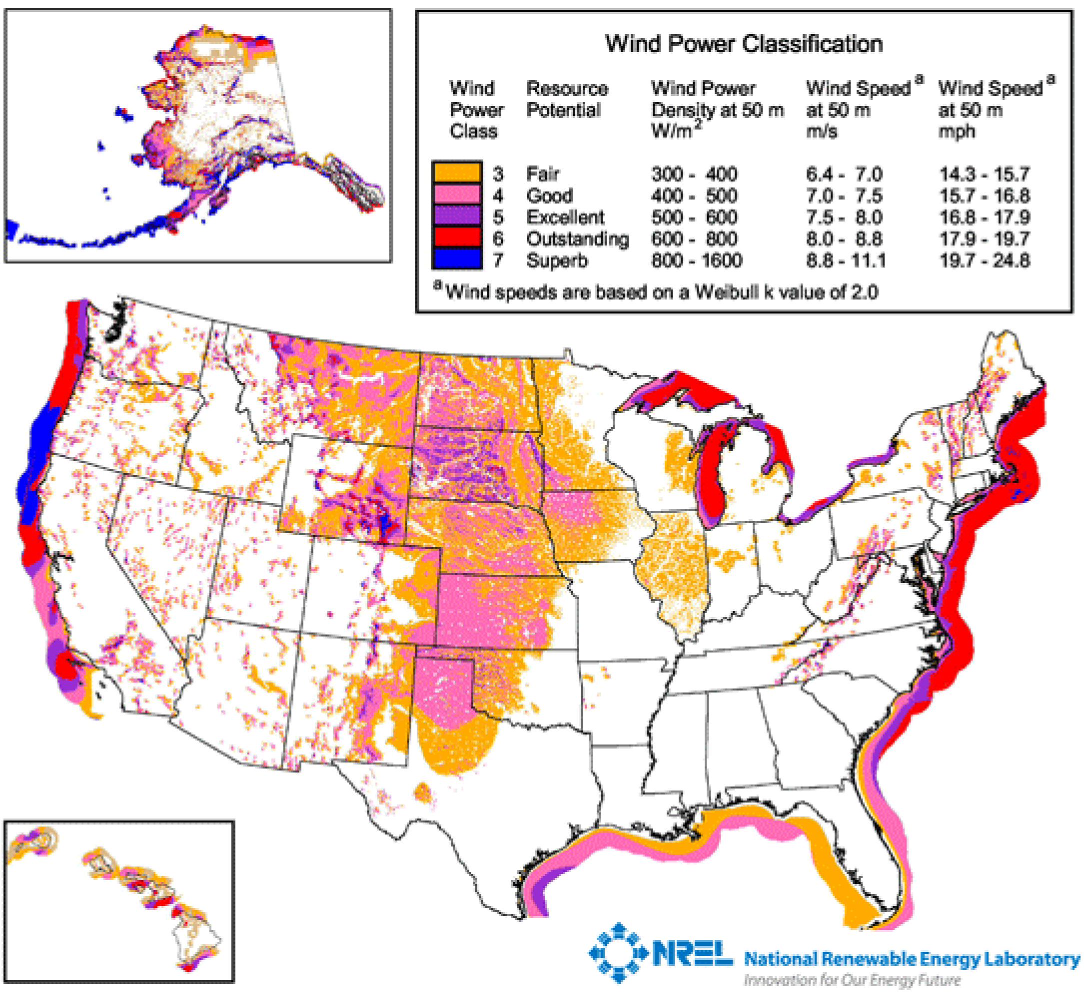

Figure 14: U.S. Wind Resource Capacity

1.2 Life Cycle Assessment

The industrial revolution was undeniably a progressive and constructive era that enabled numerous technological developments to modify agricultural practices, facilitate advancements in the technological field, and increase the production of goods/services around the world. The pre-industrial revolution era reflected abundant natural resources and a scarce population. Distinct methodologies were implemented to increase productivity of goods and services globally. Today, as the world population continues to increase with a projected nine billion by the end of the twenty-first century, the consumption of earth's resources will soon demonstrate that the industrial revolution is not sustainable over time (Allenby et al, 2010). Consequently, the next industrial revolution will be a necessary undertaking to increase resource productivity and keep up with the abundant population.

During the post-World War II era, a new generation of alternative technologies-nuclear, hydropower, geothermal and solar energy among other renewables, increased the need for a comparative analysis among these emerging replacement technologies and those in existence. As an example, the question of whether an alternative source such as nuclear power system generated more energy than it consumed led numerous investigators during the 1970's and 1980's to introduce various methods to assess the efficiency given the energy and material inputs as well as quantifying the outputs of the production system (Horne et al. 2009). Outputs may be referred to as any by-products, waste, or environmental emission(s) generated as a result of the production of a good, system, or service. As we progress towards an era where eco-friendly technologies and products gain momentum, an approach of how to quantitatively measure the

environmental burdens is crucial. At the beginning of the 1990's, the systematic evaluation titled Life Cycle Assessment (LCA) expanded to include a detailed study of the entire life cycle of a product including the environmental impacts of these emerging technologies (Allenby et al, 2010). Figure 15 illustrates the flow chart established by the International Organization for Standardization (ISO) after the 14040 standards that model the outline of a generic LCA. ISO 14040 describes the principles and the framework for a life cycle assessment (Horne et al. 2009).

The goal definition and scope of an LCA is where the system functions (primary and secondary) are defined along with the functional unit that will enable the comparison of the product or process being analyzed to other products. The assigning of the functional unit will serve as a basis throughout the study. The allocation phase also takes place in this phase since all of the inputs and outputs of the process have to be allocated to the final products. In order to keep a concise accounting of the process or item being analyzed, the elementary and reference flows also are accounted for in this stage of an LCA (Horne et al. 2009).

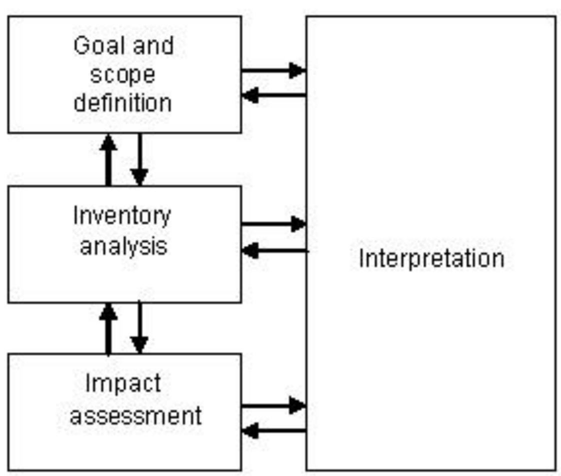

Figure 15: Flowchart of Life Cycle Assessment

In a more global scale (Niewlaar et al. 1996) identifies that the life cycle assessment of competing energy technologies reveals the potential of an alternative to achieve increased performance and decreased emissions. The life cycle impact assessment (LCIA) category includes the environmental emissions of a product or service and is typically analyzed in kilograms of carbon dioxide equivalent. The number one ranking impact assessment category is global climate change. Within that category, the Greenhouse Gases, which include: Carbon Dioxide, Methane, and Nitrous Oxide; will be used in this research.

1.2.1 Life Cycle Phases

As defined by (Hendrickson et al. 2006), the life cycle assessment studies the potential impacts throughout a product's life cycle. Figure 16 illustrates a detailed diagram of the different components for each part of a Life Cycle Assessment (LCA) study. A Life Cycle Assessment (LCA) is a systematic approach to assess the total environmental impacts associated with a product, process or service. An LCA study is also referred to as a cradle to grave analysis. It can be compared to the birth (earliest period of life) of a material/process with the accumulation of raw materials to the grave (latest period of life) or disposal stage of the item when all the materials are returned to the earth. An evaluation of the energy consumption, material inputs and additional sub processes throughout the raw material acquisition, production, usage, and disposal phases of a product are utilized for a quantitative analysis.

1.2.1.1 Raw Material Extraction Phase

Raw materials come from numerous sources. Locating each and every one of those materials involves a diverse series of inputs, outputs and processes that have impacts on the environment. The raw material extraction phase of an LCA accounts for all of the raw material

and energy quantitative amounts that are utilized for the specific product or system being analyzed. Material or energy entering the system being studied that has been drawn from the environment without previous human transformation is defined as an elementary flow. Similarly, a raw material is defined as a primary or secondary material that is used to produce a product According to (Hendrickson et al. 2006).

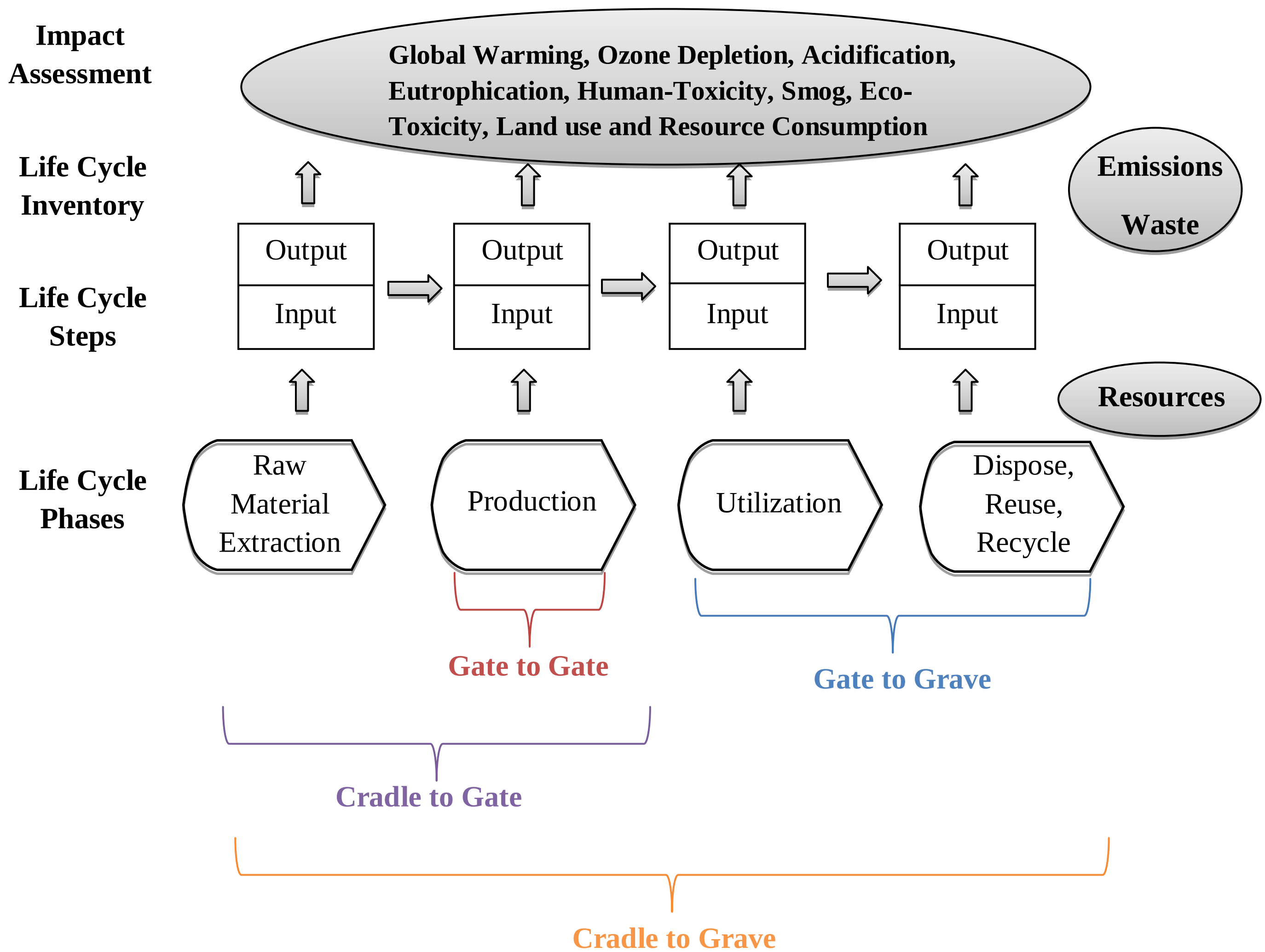

Figure 16: Detailed diagram of the components of an LCA study

1.2.1.2 Production/Manufacturing Phase

The production period is classified as the phase where the item is being manufactured and the materials and energy used in this stage are also documented. It is extremely important to consider that this stage of the development of the product there might have to also account for any by-products that might be created during this process. It is claimed (Hendrickson et al. 2006) that some challenges in the dynamic economy of today include changes in materials, designs and processes that are responsive to fluctuations ins prices, innovation technologies, regulations, and consumer preferences. Many processes in the manufacturing phase are claimed to be far from practical to analyze before the process steps are changed.

1.2.1.3 Utilization Phase

This phase is very reflective of the specified lifetime of the product or system being analyzed. Numerous assumptions are sometimes made to account for the variability and factors affecting the lifetime of a product. Countless factors might affect the years of utilization of the product or system. It is sometimes the most difficult to analyze from the four phases of the life cycle analysis. As an example, a concrete built highway lasts longer than one built with asphalt. However, the making of steel reinforced concrete consumes more energy in the manufacturing phase but during the utilization phase will wear out at a slower rate than the asphalt highway. An interesting point arises when trying to figure out how much longer a concrete highway versus an asphalt highway might have to last before it pays back the additional energy and environmental impact emission amounts.

1.2.1.4 Disposal Phase

The disposal phase of a product or system has either one of the following outcomes: disposal, reuse, or recycling of a product. In some instances, a choice is not considered from any of the three choices for the afterlife of a product. However, part of an LCA is to determine which one is more economically feasible and has fewer burdens on the environment (Lave et al. 1999).

1.2.2 Life Cycle Inventory (LCI)

The inventory analysis and this stage refers to the quantification and compilation of inputs and outputs required in a flow diagram or process tree for a certain product system throughout the life cycle system boundaries that it is being analyzed for. The total resource consumption and emissions information are catalogued in a Life Cycle Inventory (LCI) table. Later each of the life cycle phases: raw material extraction, manufacturing/production phase, utilization phase and disposal stage will be discussed in detail.

1.2.3 Life Cycle Impact Assessment (LCIA)

The third step of an LCA Study includes the impact assessment stage. This crucial stage is referred to as an evaluation of the environmental impacts of the obtained emissions in the life cycle inventory step. This phase can dictate which stage of the specific and predefined system boundaries has a larger impact in terms of emissions. Some crucial steps of the impact assessment stage include: selection and definition of impact categories, classification and characterization, normalization, grouping and weighing of the potential impacts. Some common life cycle impact categories include: Global Warming, Acidification, Eutrophication, photochemical smog, terrestrial and aquatic toxicity, stratospheric ozone depletion, human health, resource depletion, land use and water use. Overall, an LCA study is made utilizing

predefined assumptions when calculating the amounts of energy and materials utilized for the different life cycle phases.

Chapter 2: Multiple Objective Optimization Problems

Multiple Objective optimization problems or combinatorial optimization are methodologies utilized to solve complex multiple decision making problems that often involve numerous objectives or goals that are considered to be equally significant and hence makes their interaction conflictive when trying to find an optimal solution. These types of problems include various objectives to be optimized simultaneously and are recognized as multi-objective optimization problems. A general multi-objective optimization problem is represented mathematically in Equation 1.

(1)

Where:

, represent the objective functions that will be optimized.

$n \geq 2$ number of objectives

D feasible region of solutions

X decision variable space

There is no one single accurate solution to these multi-objective optimization problems but rather a set of good and feasible solutions are obtained and are called Pareto set optimal solutions or non-dominated solutions. According to (Misra & Sharma 1991) the definitions of dominated points and non-dominated points are shown below:

Definition 1: A solution x^1 is said to dominate the other solution x^2, if both conditions 1 And 2 are true:

1. The solution x^1 is no worse than x^2 in all objectives, or $f_j x^1 \leq f_j x^2$ for all j=1, 2…..M.
2. The solution x^1 is strictly better than x^2 in at least one objective, or $f_j x^1 < f_j x^2$ for at least one j = {1, 2….M}.

Definition 2: (Non-dominated set): Among a set of solutions P, the non-dominated set of solutions P' are those that are not dominated by any member of the set P.

The motivation behind a Pareto Front is to compare the obtained solutions against the rest of the solutions. Hence those solutions with the best rankings dominate the less strong solutions and become part of the dominated set.

When optimizing these types of problems, choosing the best element from some set (Pareto Front) of available alternatives for all the considered objectives is challenging and further exploration or Post Pareto optimality analysis is required.

Combinatorial optimization problems appear in a multitude of real world applications, such as scheduling, routing assignment, network design, and many other fields of utmost economic, industrial and scientific importance.

In literature, numerous methodologies have been proposed to address optimization problems that involve multiple objectives. These methods can be divided in two broad classifications: Mathematical and Meta-heuristic

Table 4: Methods to solve Multiple Objective Optimization Problems

Mathematical Methods	**Meta-heuristic Methods**
Utility Theory Functions	Particle Swarm Optimization
Goal Programming	Ant Colony Optimization
Weighted Sum Method	Evolutionary Genetic Algorithms

2.1 Mathematical Approaches

These mathematical approaches are the most common methods for solving the multi-objective optimization problems. They are primarily well-known within the evolutionary methods area because they aggregate all the distinct objectives into a single objective function.

2.1.1 Utility Theory Functions

The utility theory proposes an applied configuration for the evaluation of various options or choices made by the stakeholder. Utility can be interpreted as the satisfaction of each option provided to the decision maker. Primarily, utility theory concentrates on the assumption that a decision is made on the basis of the utility maximization principle. The utility maximization principle refers to selecting the best choice that is based on the choice that provides the maximum utility or benefit to the stakeholder or decision maker.

Utility theory is an area of decision making analysis that considers various mathematical models to influence choice behavior in ambiguous circumstances. Primarily, it aims to mimic how people make decisions in the presence of certain risk factors.

Utility theory function is also referred to as value function and it is a mathematical expression that assigns a value to all probable choices. These approaches are extremely notable methods to solve multi criteria problems when an explicit mathematical formulation for the value function is known. Equation 2 below illustrates the general formulation for a utility function.

(2)

2.1.2 Goal Programming

Charnes et al. (1955) first presented goal programming. It is a general linear programming model that is apt to various multiple objectives and the aim is to minimize the deviations from the stated goal of the decision maker. The advantage of goal programming includes the ability to handle enormous amounts of objectives, constraints and objectives. However, a drawback is that it has a tendency to have results that are not part of the Pareto front.

Ogryczak (1994) proposed a newer version of previous weighted min-max approach by Gembick (1974). In this work, Ogryczak published a version that utilizes an aspiration point.

A general formulation for a Goal Programming problem is shown in Equation 3 below.

(3)

Where $x_{1,}$ $x_{2,\ldots,}$ x_n are the decision variables, and $c_{1,}$ $c_{2,\ldots,}$ c_n are the contribution coefficients. Each characterizes the contribution to the minimization of Z for each of the objective functions. In this case, $a_{i,j}$ is the constraint and it represents the coefficients that characterizes the per unit usage by x_i of coefficient of b_j. These coefficients are parameters that must be known. It is important to note that each unit for the decision variable x_i contributes c_i units to the objective function.

The goal programming method is one of the most widely used to solve multiple objective optimization problems but again for more difficult problems it will not find feasible results. Additionally, it does not optimize all the objectives simultaneously.

2.1.3 Weighted Sum Method

The weighted sum method (WSM) was first proposed in 1967 by Fishburn. First, the priority of the objectives is calculated and compared to the other alternatives with the max weighted summation method. Some difficulties imposed by this are the lack of being able to find a Pareto set in the search space (Das & Dennis 1997). Equation 4 below illustrates the general formulation for the WS method

(3)

In this case,

w_i: represents the weight assigned for each objective.

2.2 Meta-heuristic Approaches

A Meta-heuristic can also be defined as a high-level algorithmic framework or approach that can be specialized to solve optimization problems (Black 2009). Meta-heuristic methods have demonstrated to find good approximations to a global optimal in very complex problems where mathematical methods cannot be implemented. Numerous meta-heuristic approaches such as, Ant Colony, Particle Swarm, and Genetic Algorithms have been widely used recently with successful applications in different areas, such as: optimization in scheduling, facility layout, supply chain management, maintenance policy selection, assembly line optimization, among others.

2.2.1 Particle Swarm Optimization

Particle swarm optimization (PSO) was first introduced by Kennedy and Eberhart in 1995. It tends to mimic the behavior of organisms such as fish and bird flocking. This PSO method is a population based method like the Genetic Algorithms (GA's). However, this method promotes mutual cooperation. In PSO, each single solution is a bird or particle in the search

space. In this case, all of the particles have fitness values assigned which are evaluated by the fitness function to be optimized.

The PSO algorithm is started with a group of random particles (solutions) and then searches for the optima by updating generations. At every iteration each particle is updated by the two greatest values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another good value that it is evaluated by is the particle swarm optimizer. This is the best value obtained so far by any particle in the population. This best value is a global best and is then called gbest. When a particle breaks apart from the population, the best value is a local best and is called lbest.

The PSO algorithm can be described as follows

1) For each particle, the position and velocity vectors will be randomly initialized according to the same size as the problem dimension.
2) Measure the fitness of each particle (*pbest*) and store the particle with the best fitness (*gbest*) value.
3) Update velocity and position vectors according to steps (1) and (2) for each particle.
4) Repeat steps 2–3 until a termination criterion is satisfied.

There have been various updated versions to the PSO problem which include the addition of an inertia weight (Shi & Eberhart 1998) and the proposed constriction coefficients by Clerc (1999). The latest edition in 2002 by Mendes is titled fully informed particle swarm (FLIP) and it claims to have a measure that illustrates that the particle is affected by the surrounding neighbors.

2.2.2. Ant Colony Optimization

The ant colony optimization (ACO) algorithm is also a meta-heuristic search method based on the behavior of ants when looking for food. During this process, the ants tend to deposit a pheromone trail to leave a mark on the shortest path for other members of the ant colony to follow. This algorithm was proposed in 1992 by Dorigo. The less amount of time the ant takes to travel again through that same trail the least amount of pheromone will disappear. Obviously, the shorter path is traveled on the most and hence has higher pheromone density (Mullen 2009). The ant colony process is described briefly as the following:

1.) One ant finds the food source, then returns to the nest. It leaves behind a trail of pheromone.
2.) The shortest path soon becomes the most popular as a result of the pheromone trail intensity.
3.) As more ants travel the shortest path, the longer trails lose the tail of pheromone and eventually minimize the ant travel through there.

Several applications of the ACO algorithm include the vehicle routing problem (Gambardella & Thaillard, 1999) and the job shop scheduling problem (Colorni et al. 1994).

2.2.3 Evolutionary Genetic Algorithms

Evolutionary Genetic Algorithms are based on how biological evolution works. J.H. Holland first proposed this method. First, an initial random population is generated. Then, selection processing occurs where only the strongest or the survival of the fittest occurs to be

parents of the following generation. The elite parents reproduce a new population is created and this continues until the specific stopping criterion is met.

Numerous evolutionary algorithms have been proposed to solve multiple objective optimization problems. Some of those algorithms include:

- NSGA (Non-dominated Sorting Genetic Algorithm) by Srinivas and Deb (1995).
- SPEA (Strength Pareto Evolutionary Algorithm) by Zitzler andThiele (1999).
- PAES (Pareto Archived Evolutionary Algorithm) by Knowles and Corne (2000).
- NSGA-II (Non-dominated Sorting Genetic Algorithm) by Deb et al (2002).

2.2.3.1 Pareto Archived Evolutionary Algorithms (PAES)

Knowles and Corne developed the Pareto Archived Evolutionary Algorithm in 2000. This algorithm has the crossover phase completely different from the other algorithms. It starts off with a parent generating one offspring by mutation. In the case the offspring dominates the parent, the offspring is automatically added to the parent pool and the iterations continue. On the contrary, if the parent dominates the offspring, the offspring is discarded and a new offspring is generated. A comparison set of the previously non-dominated individuals is used in the case that neither dominate each other. Diversity along the Pareto set is of utter importance and to address this, the algorithm stores an archive of non-dominated solutions. The new offspring population is compared with those solutions in the archive to verify if it dominates any member of this set. If indeed it does dominate a solution in the archive then the offspring is classified as a new parent. Automatically, the dominated solutions are eliminated from the archive. However, if the offspring does not dominate any member of the archive, both parent and offspring solutions are checked for their distance with the solutions of the archive. If the offspring resides in the least

crowded region of the parameter space among the members of the archive, it is becomes a parent and a copy is added to the archive.

2.2.3.2 Strength Pareto Evolutionary Algorithm (SPEA) I and II

The Strength Pareto Evolutionary Algorithm (SPEA) was developed by Zitzler and Thiele in 1999 with the secondary improved version SPEA II in 2001. This algorithm is quite similar to other evolutionary algorithms. However, it retains an external population after every generation storing all non- dominated solutions obtained so far. After every generation, both the external and current populations are mixed to attain a new set. It is more explicit in the sense that the non- dominated solutions in the mixed population are assigned a fitness rank based on the number of solutions they dominate. Those that dominate more solutions have a superior rank. To ensure diversity among the non-dominated solutions, a clustering method is utilized to achieve this.

The second version of the Strength Pareto Evolutionary Algorithm (SPEA II) was proposed in 2001 by Zitzler, Laumanns and Thiele. The variant of the first version, assigns all of the non-dominated solutions from the current and external population groups to the next population after a fitness evaluation. This allows for more variability within the set. In the case that the current population is less than the allowed population size, then it is filled with non-dominated individuals from both sets. SPEA II is different in the sense that it uses a fine-grained fitness assignment that integrates density information and hence identifies individuals that have identical fitness values.

2.2.3.3 Non-Sorting Genetic Algorithm (NSGA) I and II

The Non-Sorting Genetic Algorithm was first developed by K. Deb in 1995 and a better second version was published in 2002 (NSGA-II). First, a random population is created based on non-domination. According to the non-domination rank, each solution is assigned a fitness value. A children population is created with binary tournament selection and mutation are used to create a children population. A combined population is also made from the parent and offspring population utilizing the concept of elitism. Then, the combined population is sorted and ranked based on the non-domination theory. An elite parent population continues to update by adding the first front solutions and so forth until the population size has been exceeded. Crowding distance comparison enables the population reduction and the tournament selection is used for selecting the best.

Chapter 3: Redundancy Allocation Problem (RAP)

The RAP [Kim & Yum, 1993] is one of the most studied reliability optimization problems. The system is composed by *k*-out-of-*n* components which are required to be in operation to avoid failures in the system. The system can be built out of several available components. Each component has its own reliability and an associated cost. Some additional information consists on the carbon dioxide, methane, and nitrous oxide emissions that are emitted if that component is built. The usage phase is not considered in the data. Figure 17 displays a general series-parallel system. It contains a total of *s* subsystems arranged in series. Additionally, for each subsystem illustrated there are components with different levels of reliability, cost, and environmental emissions. There are available components and only components will be selected. For each subsystem *i*, a minimum number of components must be chosen.

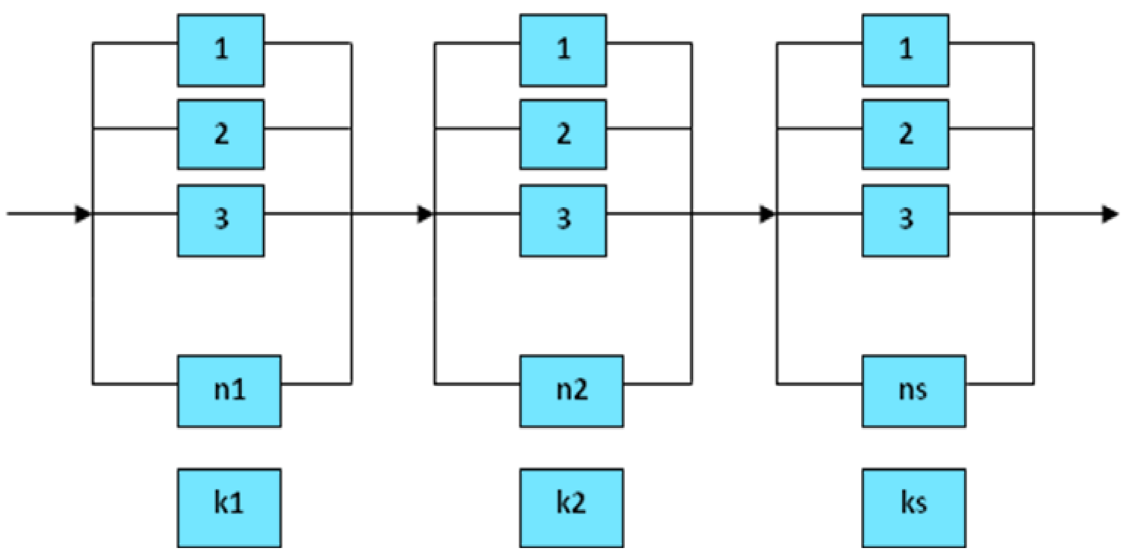

Figure 17: Example of a RAP series-parallel structure

3.1 Single Objective Redundancy Allocation Problem

Fyffe et al. (1968) published a paper where he used genetic algorithms to solve the Redundancy Allocation Problem (RAP). Later Ant Colony Optimization was utilized by Liang and Smith (2004) to effectively solve the RAP with an adaptive penalty method. Then, in 2007, Nahas et al. utilized a hybrid ant colony optimization method with a degraded ceiling local search technique that performs better than the previously mentioned methods. Coit & Smith (1996) published a genetic penalty guided algorithm that searches both feasible and unfeasible regions to find optimal solutions. Again Coit & Smith (1996 b) recommended a hybrid genetic algorithm and a neural network to identify optimal levels of redundancy while the neural network identified optimal reliability levels. In Yokota et al. (1996) a non-linear mixed integer programming problem is solved using genetic algorithm with an aggregated penalty function. In a more recent work, Beji et al. (2010) present a hybrid algorithm with a local search algorithm and a particle swarm optimization algorithm. It aggregates an adaptive penalty function that encourages exploring near the feasible region until a solution is present. This hybrid algorithm is a variation of three distinct problems and compared to popular methods such as Multiple Weighted Objectives and Tabu Search solutions. In another work, the RAP is modified from a multi-objective problem to a single objective optimization problem (Dhingra 1992). Then, goal programming is used to decide which objective has the highest ranking weight and solve the optimization problem as a single objective. Finally, the constraints are utilized to limit the search space and attain a suitable solution.

3.2 Multiple Objective Redundancy Allocation Problem

Some of the most recent works in the multi-objective redundancy allocation problem include Liang & Lo (2010). They presented a variable neighborhood search (VNS) algorithm to solve the multiple objective redundancy allocation problems. There are three different problems that are presented to illustrate the capacity of the algorithm. In the first example, reliability is maximized and cost is minimized with a constraint to weight and volume. The second example has the objective of maximizing reliability and minimizes cost and a constraint to weight. The third example has the objectives of maximizing reliability and minimizes weight and the constraint is cost. The results showed that this algorithm is able to generate more non-dominated solutions in an extremely efficient way. Soylu & Ulusoy (2011) proposed the τ- neighborhood approach to increase the number of references. The proposed approach solved a double objective redundancy allocation problem. The objectives were to maximize the subsystem's reliability and minimize the overall system cost. The problem was solved with the €-constraint approach and the Pareto optimal solutions were found. After that, a post-pareto optimal analysis was conducted to attain the best set of solutions of the problem. Other promising approaches include (Taboada & Coit 2010) where a new multi-objective evolutionary algorithm is proposed for solving optimally the redundancy allocation problem. This work utilizes a genetic algorithm (GA) based on elitist reinsertion, a rank selection and modifying genetic operator constraint handling method. Hybrid approaches are also extremely popular today. Some of these hybrid techniques t utilize a combination of mathematical and metaheuristics approaches that have been created and combines them for experimentation. As an example, (Tian and Zuo 2006) combined genetic algorithms and various dynamic programming techniques to try and locate an optimal solution to the multiple objective redundancy allocation problem.

Chapter 4: New Multi-objective RAP formulation using NSGA-II and Illustrative Example

4.1 Multi-objective RAP formulation with environmental emissions using NSGA-II

In numerous case studies, the RAP has been solved as a single objective optimization by aggregating two objectives (cost and reliability) into one (Kuo & Wan 2007). However, this aggregation might disregard the possibility of encountering non-dominated solutions in the Pareto-optimal front. Several approaches have been attempted to solve the RAP as a multiple objective optimization problem (Ramirez-Marquez & Coit 2004) and (Liang & Smith 2004). In (Taboada et al. 2008) an introduction of a multiple objective genetic algorithm was presented to solve this optimization problem with two conflicting objectives. The MOMS-GA was proposed to solve the RAP taking into account the system availability, cost and weight.

The following notation will be used in the remainder of this paper:

Notation(s):

$_j$) = reliability for the available component in subsystem *i*

$\boldsymbol{x_{ij}}$ **=** quantity of the available component used in subsystem *i*

= cost for the available component in subsystem *i*

= emissions in kilograms of carbon dioxide of the available component in subsystem *i*

= Global Warming Potential of greenhouse gas type *r*

= emissions in kilograms of greenhouse gas type *r*

Where E_1 = Carbon Dioxide,

E_2 = Methane,

E_3 = Nitrous Oxide,

= minimum number of components in parallel required for subsystem *i* to operate

s = number of subsystems

= total number of available components for subsystem i

= user defined maximum number of components in parallel used in subsystem i

Equation 1 illustrates how the RAP was formulated and used in this paper

(4)

Subject to:

$\leq \quad \leq \quad$ for $\quad i = 1, 2,\ldots s$

$\varepsilon \{0, 1, 2,\ldots\}$

Where:

(5)

Table 5: Global Warming Potential of selected Greenhouse Gases

Green House Gas (GHG)	Global Warming Potential (GWP)/kg of GHG
Carbon Dioxide,	1
Methane,	21
Nitrous Oxide,	310

4.2 Illustrative Example

The reader can refer to (Taboada & Coit 2006) for the particular reliability and cost component values used. The different data of emissions released by the design of each available component was added in this paper. Since the three different gases can be aggregated into Global Warming Potential, this one represents our third objective. The example considered consists of three subsystems with a choice of five, four, and five different types of components in each subsystem. The maximum allowable number of components in each subsystem is eight for this example. For this paper, the values of E_1, E_2 and E_3 were generated by multiplying the GWP value provided in Table 5.and a randomly generated amount of carbon dioxide equivalent kilograms. All values for E_1, E_2 and E_3 were rounded to the nearest integer. The data in Table 6 represents the data that was input to the NSGA-II algorithm.

Table 6: Component selections for each subsystem

Design alternative *j*	**Subsystem *i***														
	1					2					3				
	R_{ij}	C_{ij}	E_1	E_2	E_3	R_{ij}	C_{ij}	E_1	E_2	E_3	R_{ij}	C_{ij}	E_1	E_2	E_3
1	0.94	9	12	15	9	0.97	11	13	6	1	0.96	10	3	20	29
2	0.91	6	11	31	8	0.86	3	16	19	4	0.89	6	11	8	6
3	0.89	6	10	14	9	0.70	2	23	5	7	0.72	4	13	7	10
4	0.75	3	9	7	12	0.66	2	4	26	9	0.71	3	29	15	25
5	0.72	2	12	11	13						0.67	2	9	31	17

This algorithm was run for 100 generations and Figure 18 shows the obtained Pareto-optimal set. Once the Pareto set has been obtained, post-Pareto optimality methods can be used to select one solution for system implementation to obtain a smaller number of solutions. However, post-Pareto optimality is out of scope for this work and will be considered for future work.

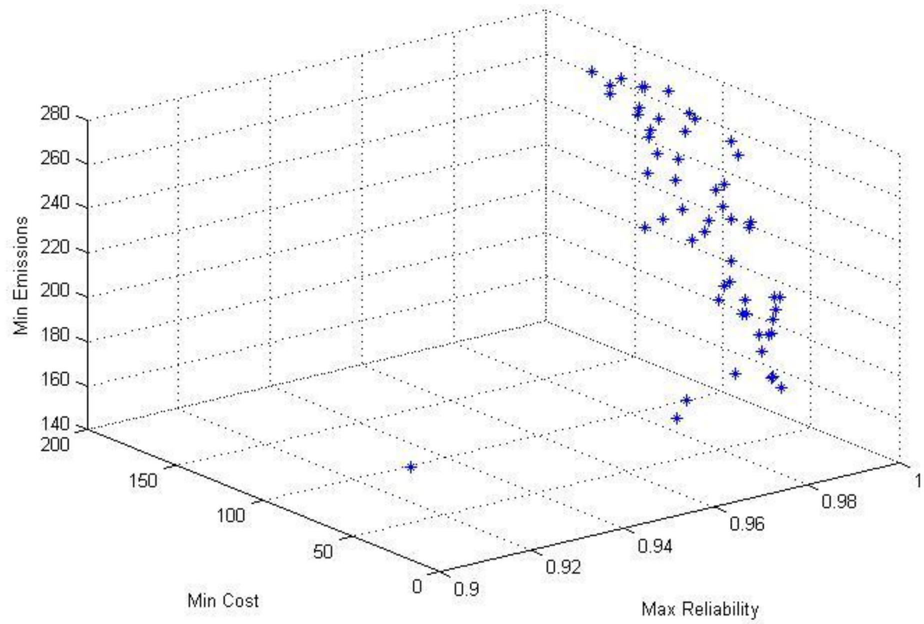

Figure 18: Pareto-optimal set of solutions obtained with NSGA-II algorithm

In order to provide a solution to the decision maker, the closest solution to the ideal point [1, 0, 0] which denotes a reliability of one and cost and environmental emissions equal to zero was selected. The selected solution and the corresponding objective values are shown in Table 7 and table 8 respectively. In order to choose the point from among the Pareto front as the closest to the ideal point, a Euclidean distance was calculated. The point with the shortest distance to the ideal point was chosen and the selected system configuration is shown in Figure 19 and Tables 7 and 8 with the respective reliability, cost and emission values. For the selected system configuration, not all of the components were utilized to generate the selected objective function values of system as can be observed by the two following tables.

Table 7: Selected configuration of system

Subsytem 1							
component 1	component 2	component 3	component 4	component 5	component 6	component 7	component 8
5	1	2	1	3	0	0	0
Subsytem 2							
component 1	component 2	component 3	component 4	component 5	component 6	component 7	component 8
3	3	1	1	1	0	0	0
Subsytem 3							
component 1	component 2	component 3	component 4	component 5	component 6	component 7	component 8
2	4	2	4	3	5	2	1

Table 8: Objective values of selected system configuration

Reliability	Cost	Emission
0.999074183	83	150

As shown in the previous example, the NSGA-II algorithm delivered the optimal Pareto front results. For this specific problem formulation, the pareto front or non-dominated solutions were found. The selected values of the system configuration in Figure 19 below illustrate the best system design configuration that is closes to the ideal point of [1, 0, 0] and does not put in jeopardy the values of the other objectives. This figure shows that for the first two subsystems, only five components were used whereas in the third subsystem the eight were fully utilized. There are numerous post-pareto optimality measures. Among the most recent and popular techniques is the utilization of a clustering technique for the instances when the Pareto-optimal set is quite large or in certain cases contain an infinite number of solutions. In this work, (Taboada & Coit, 2007) the Pareto-optimal set is pruned to obtain a smaller multi-objective design space and hence the decision maker can select a final design solution with minimal trade-offs. In another method, a clustering method based on dynamic self-organizing trees for Post-

pareto optimality analysis proposes two main advantages. First, it eliminates the need to provide an initial number of clusters and the algorithm optimizes the number of clusters at each hierarchical level. This also enables the reassigning of data from being misclustered. Another work, (Venkat et al., 2004) proposed and analyzed a Greedy Reduction (GR) algorithm that obtains clusters or subsets of Pareto optimal solutions from the large solution sets in multi-objective optimization. The choosing of these subsets is based on maximizing a scalarizing function of the vector of percentile rankings of the Pareto solutions within the larger set.

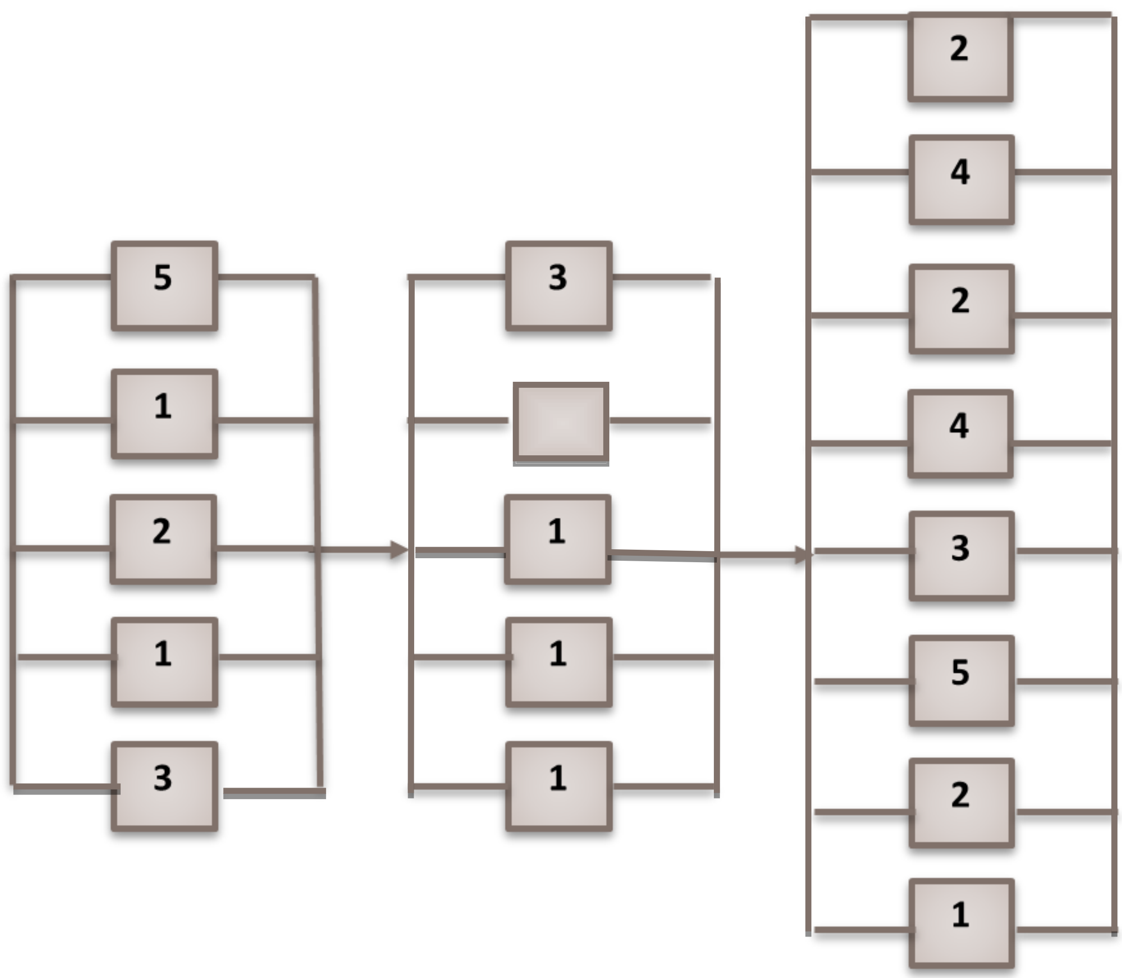

Figure 19: Selected System Configuration

Chapter 5: Conclusions and Future Research

In this paper, an approach was presented to solve a multi-objective redundancy allocation problem with NSGA-II algorithm. Numerous studies have solved the RAP by maximizing the reliability, minimizing the cost and minimizing the weight of the system. However, this paper focused on simultaneously solving the conflicting objectives of maximizing the system reliability and minimizing the cost and environmental carbon dioxide equivalent emissions. The emissions generated in other phases of the system's life cycle will be explored as future research upon expansion of the system's boundaries. The presented work obtained a set of non-dominated solutions and is considered optimal for this particular series-parallel system configuration. Post pareto optimality represents an extremely important factor of any multiple objective optimization problem since this is where the optimal solution is acquired. Nevertheless, post-pareto analysis is not part of this work but due to the large factor of influence it will be considered as future work as the system boundaries are expanded for further analysis of different system configurations.

As part of future research, the system boundaries will be expanded to solve for the remaining life cycle phases which include: raw material extraction, utilization, and disposable phases. These remaining phases can be formulated and coded as an accelerated life testing reliability optimization problem. In the accelerated life testing problem, there are two types of analysis. These include a time-step test and a failure-step test. A time-step test runs a specified time at the first stress, and a failure-step test runs until a specified proportion of units fail at the first stress. This is quite useful for modeling the utilization phase of a product or system because the useful time of functionality depends on a predefined constraint. As an example, airplane parts have a certain median life and accelerated life testing involves the much needed information on the life expectancy of materials. Some examples of accelerated test conditions include larger

amounts of pressure, temperature, voltage, vibration and load. Many are modeled as single parameters but other studies have combined these test conditions for analysis.

Another feature to consider for future research includes the analysis of other impact assessment methodologies such as ozone depletion, smog, acidification, eutrophication and human toxicity among others. For example, the minimization of eutrophication in water consists of lower levels of phosphorus and nitrogen instead of the carbon dioxide equivalent measure utilized in this research. Acidification is measured in sulphate levels and hence can be modeled in a similar manner to eutrophication.

Overall, the main future research objective is to be able to analyze the various phases of a life cycle of a product/system in terms of the many impact assessment categories that exist to model precisely the entire life cycle and the respective emissions to be able to model the redundancy allocation problem. As a result, a specific multi-objective evolutionary algorithm (MOEA) will be proposed to solve this type of redundancy allocation problems.

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Vitae

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